NORGES HANDELSHØYSKOLE

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Behind the Hedge

A Closer Study of Nordic Hedge Funds

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This thesis was written as a part of the Master of Science in Economics and Business Administration program - Major in Financial Economics. Neither the institution, nor the advisor is responsible for the theories and methods used, or the results and conclusions drawn, through the approval of this thesis.

Foreword

This thesis is written in conjunction with my final semester as a Master student at the Norwegian School of Economics and Business Administration (NHH). My specialization is in finance, and this thesis has been a great way for my to express some of what I have learned. Even though it has been a long and sometimes very challenging process writing this thesis, I have really enjoyed it and learned a lot about the hedge fund industry.

The choice of topic for this thesis was decided in cooperation with DnB NOR Asset Management. After a job interview with their quantitative trading team, a list of possible topics was sent to me. One of them was about Nordic hedge funds. Since these kinds of funds were already something I was very interested in, the choice of topic was in the end pretty simple.

There are a few persons that I would like to express my gratitude towards who has been very helpful in completing this thesis. First of all I would like to thank my advisor at NHH, Associate Professor Tommy Stamland, for all the constructive comments and helpful advices. I would also like to thank Michael Fowler at HedgeNordic.com who has answered all my questions about Nordic hedge funds and the database. Last, but not least, I would like to send a huge thanks to Espen Lundstrøm and his Global Quant team at DnB NOR Asset Management. They have been so very kind to allow me to spend some of their valuable time extracting data and asking a lot of questions!

Bergen, 13 June 2007

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Abstract

This Master thesis is dedicated to the performance of Nordic hedge funds. A lot of international studies have been conducted on American hedge funds, but little on Nordic funds. Common for most of these studies are that hedge funds perform very well compared to other more traditional assets like stocks and bonds, but that the risk in hedge funds are somewhat different and usually not captured by traditional financial theory. Hedge funds often exhibit significant higher order moments while traditional theory only takes into account the first two moments of the return distribution.

This thesis shows that Nordic hedge funds outperform both American hedge funds and the general stock and bond markets. They have better distributional properties and risk-adjusted performance measures. The correlation to the stock and bond market is also relatively low for Nordic hedge funds, even in bear markets and during financial crises. This offers good diversification benefits, and an optimal portfolio of hedge funds should consist of around 17-18 individual funds.

Some of this good risk-adjusted performance can however be attributed to general stock and bond market exposure. This is not consistent with the notion that hedge funds are on average market neutral. The returns are also influenced by some fund specific factors like for instance assets under management, age, fees and investment universe. But the good performance of Nordic hedge funds does not seem to be due to pure luck, but rather manager skills. This is backed up by the fact that there exists persistence in the hedge fund returns, especially at shorter horizons (3-6 months).

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1. Introduction

1.1. Problem definition

The main purpose of this thesis is to take a closer look at the risk and return characteristics of Nordic hedge funds. Is the risk and return in these hedge funds different from other hedge funds around the world, or from other asset classes? If so, how can this be exploited in asset management? Is it possible to identify sources of hedge fund return and risk, and if so, can these sources be replicated in some way? Are there any differences between the different styles? These and some other questions will be answered by conducting a number of empirical tests on a sample of 107 individual Nordic hedge funds as well as a sample of American hedge fund indices.

After some preliminary theory, this thesis will start off with a brief summary of the descriptive statistics of hedge fund returns. Other studies[1] have concluded that the risk-return relationship looks particularly good for foreign hedge funds if one only considers the two first moments of the return distribution. But this advantage is blurred if one also takes into account higher order moments. Hedge fund returns often exhibits low skewness and high excess kurtosis, and this will be checked for in the Nordic sample.

Despite the fact that the risk-return relationship of hedge funds is not as superior as first thought, they have in the recent years become increasingly more popular among institutional investors. Why is that? One of the most important reasons for this is the way hedge fund returns interrelate with the returns from other major asset classes like the equity and fixed income market. Research[2] has shown that the correlation between hedge fund returns and stock and bond returns are quite low. This leads to a major diversification benefit from adding hedge funds to a portfolio. In this thesis these

[1] See for instance Kat and Lu (2002) and Brooks and Kat (2002).
[2] See for instance Fung and Hsieh (2001) and Agarwal and Naik (2004).

coefficients will be calculated for different market environments, and in addition a Monte Carlo simulation will be used to find out how many hedge funds are needed to achieve the optimal portfolio of hedge funds.

Furthermore, this thesis will use different measurements to compare the performance between hedge funds and the equity, bond and commodity markets. Many of these measures rely heavily on the assumption that the returns are normally distributed. But that is rarely the case, especially for hedge funds. This has lead to the development of new measurements that also takes higher order moments into account. The Spearman rank coefficient will also be used to see if these performance measurements produce significantly different rankings.

The fact that hedge fund return characteristics are so different from other asset classes, have lead different asset pricing models to predict their returns poorly. In this thesis the predictive power of five such models are tested.

Some studies[3] have been conducted on which factors that drives the performance of hedge funds. This thesis will run rigorous models in order to try to find significant factors, both macro and micro, that explains hedge fund return and risk. The analysis will be applied to both individual funds and indices.

Historically, it seems that some factors have played an important role in describing hedge fund returns. This has recently lead to the creation of a new market for large investment banks, namely hedge fund replication. By loading up with the specific risk factors that hedge funds are exposed to, they can replicate their returns pretty closely. This is called *Alternative Beta*. In addition, recent research[4] has started using option based replication of hedge fund returns. Both these techniques will be shortly reviewed towards the end of this thesis.

[3] See for instance Ackermann et. al. (1999), Anjilvel et. al. (2001) and De Souza and Gokcan (2003).
[4] See for instance Fung and Hsieh (2001) and Agarwal and Naik (2004).

The last subject that will be covered in this thesis is the consistency of hedge fund performance. Is the good performance of hedge funds only due to some extreme events or luck, or is it consistent through time? In addition to some statistical tests, the approach of Jegadeesh and Titman (1993, 2001) will be used to see if there is any momentum in individual hedge fund returns.

1.2. Structure of thesis

The rest of the thesis will be organized in three main parts. The first part, consisting of chapter 2-4, will present some preliminary theory about hedge funds and traditional portfolio management in addition to a short presentation of the data used in this thesis. The second part, chapter 5-12, will cover the empirical part of this thesis. And the final part, which consists of chapter 13 and 14, will round up this thesis by reviewing some possible bias before concluding.

2. A Short Introduction to Hedge Funds

2.1. What is a Hedge Fund?

According to Mark Anson, CEO of Hermes Pensions Management, the answer to that may be “Anything that charges 2 and 20.” (Lhabitant, 2006). This is an old joke, and the “2 and 20” refers to the fee structure of hedge funds. They often charge a 2% management fee and a 20% incentive or performance fee. Due to their complexity, the term “hedge fund” does not have a precise definition. There exist many types of definitions, for instance this one by Lhabitant (2004):

“Hedge funds are privately organized, loosely regulated and professionally managed pools of capital not widely available to the public.”

Due to their private nature, hedge funds have fewer restrictions than regular mutual funds. They can use leverage, short-selling and derivatives, and this allows them to follow significantly different investment strategies. The main strategies, or *styles*, will be discussed later in this chapter.

Hedge funds are not an asset class by itself, but more an alternative investment vehicle just like real estate and private equity. They seek to provide the investors with absolute return (or relative to cash), in contrast to mutual funds who are measured relative to a proper benchmark.

2.2. The history of Hedge Funds

It has long been believed that the first hedge fund was established by the Australian Alfred Winslow Jones in 1949. But according to Lhabitant (2006) resent research indicated that this is not entirely correct. In December 1930 the statistician Karl Karsten created a small fund that looked much like a hedge fund. In just under six months the fund generated a 78% return.

The Melbourne born Australian Alfred Winslow Jones set up the first more formally hedge fund in 1949. He raised $100,000 (including $40,000 of his own money) to form a general partnership named A.W. Jones & Co. (Lhabitant, 2006). He discovered that he could use short-selling and leverage to create a better return than regular mutual funds. And an article by Carol J. Loomis (1966) confirmed this. The article showed that Jones' fund had outperformed the most successful mutual funds in the period from 1955-1965. Jones' fund returned a staggering 670%, compared to the 358% of the Dreyfuss fund.

In the years following Jones' start, many other future industry leaders started their hedge funds. One of them was probably the greatest investors ever, Warren Buffett. In 1956 he established Buffett Partnership LP who later became Berkshire Hathaway (in 1962). The performance of Berkshire has for the last 40 years been absolutely stunning, with an average annual return of around 21.5% (Lhabitant, 2006).

In the period from 1969 to 1974 many hedge funds went bankrupt. This was much due to inexperienced short-selling (Lhabitant, 2006). During the bull markets of the 1960's many fund managers who was supposed to follow a long/short strategy started going long only and levering up. When the bear market of 1969-1970 kicked in, many hedge funds collapsed. And even more funds collapsed during the 1973-1974 recession.

The popularity of hedge funds was revived again in 1986 when an article describing the tremendous performance of the Tiger Fund was published in *Institutional Investor*[5]. But then it all went very bad on 19 October 1987, also known as "Black Monday". The Dow Jones was down 22.6% and many hedge funds also suffered huge losses (Lhabitant, 2006). But luckily the market recovered quickly, and by 1989 the market had regained all the lost ground.

[5] See J. Rohrer (1986).

1997 and 1998 were some tough years for the hedge fund industry. Global macro funds were blamed for the 1997 Asian crisis, and fund managers were described as "wild-eyed speculators operating outside government regulations" (Lhabitant, 2006). But the landmark incidence in the evolution of the hedge fund industry came in August 1998 when Long-Term Capital Management (LTCM) collapsed. The funds board of directors included two Nobel price winners, Myron Scholes and Robert C. Merton, and the fund had been extremely successful in its first years. They used advanced mathematical models to perform fixed income arbitrage with government bonds (Wikipedia, 2007). But the models were not able to forecast what was going to happen on 17 August 1998. Then the Russian government devalued the rouble and defaulted on its domestic debt. LTCM were long Russian government bonds and short US Treasuries bonds. This Russian incident lead to a *flight-to-liquidity*[6] situation where everybody wanted to buy US Treasuries. Then LTCM lost enormous amounts on *both* their positions, and by the end of August the fund had lost $1.85 billion of its capital (Wikipedia, 2007). For the first time in history, a hedge fund was deemed "too big to fail", and a consortium of 14 banks and security firms put together a $3.5 billion bailout of the fund (Lhabitant, 2006). All this was orchestrated by the New York Fed who was afraid of a global financial meltdown if LTCM went bankrupt. The fund was finally closed down in early 2000 (Wikipedia, 2007). The reason for the collapse of LTCM was not the Russian default in itself, but rather the excess use of leverage from LTCM's side. At the beginning of 1998 the fund had $4.72 billion in equity and it had borrowed over $124.5 billion. But something good came out of this crisis, and that was that hedge fund mangers agreed to lower leverage and induce more transparency.

The crisis of 1997-1998 lead the US Fed to cut interest rates, and this again fueled the US economy in the years following. Because of these good conditions for the financial market and especially riskier assets (like the IT-sector), a bubble developed. And in March 2000 it burst. Despite the fact that major indices performed very bad, the hedge fund industry performed very well. This lead many high net worth investors to get into

[6] *Flight-to-liquidity* means that "everybody" wants to buy highly liquid securities, like for instance US Treasuries bonds.

hedge funds, and hedge funds were gaining popularity among large institutional investors.

The growth in the hedge fund industry has accelerated dramatically the last 15-16 years (figure 2.1). According to HFR[7] there are around 9,575 hedge funds world wide as of March 2007, and their assets under management (AUM) are around 1.57 trillion dollars[8]. But despite its rapid growth, the industry only accounts for 2-3% of the global financial market (Lhabitant, 2006).

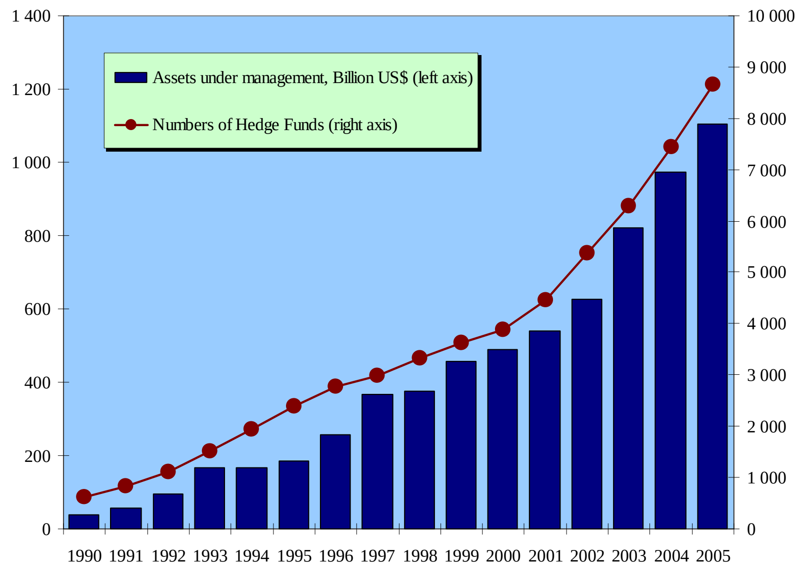

Figure 2.1: Estimated assets under management and number of hedge funds in the period 1990-2005 (Lhabitant, 2006).

The major source of future growth in the hedge fund industry is from large institutional investors like pension funds, insurance companies, corporations and foundations. A sign of this came in 2000 when Calpers (California Public Employees Retirement System) decided to allocate $1 billion to hedge funds (Lhabitant, 2006).

[7] E-mail from Todd Hartman at HFR, 16.05.07.
[8] According to Dagens Næringsliv (2007b).

2.3. Why Hedge Funds?

There are mainly two reasons why investors allocate money to hedge funds. Firstly, hedge funds have historically (with a few exceptions like i.e. LTCM) shown a much better risk/reward relationship than other assets (at least in the mean/variance framework). Secondly, they have historically had a low correlation to the general stock and bond markets. This offers the investors a diversification benefit. Later in this thesis both these benefits will be explored for the Nordic hedge fund market.

Furthermore, hedge fund managers have fewer restrictions in their asset management than regular active fund managers. This makes them able to generate alpha in ways that traditional active fund managers can not. Most important is the fact that hedge fund managers can sell assets short. Active managers can only underweight assets according to their benchmark. Figure 2.2 shows how this can reduce the risk (standard deviation) for the hedge fund manager, without decreasing the expected return of the portfolio. As long as one asset has a negative expected return, the hedge fund manager can go short this asset and in the hypothetical example in figure 2.2 the manager can then reduce its risk by over one percentage point (from 5.52% to 4.45%).

	Covariance matrix			Expected
	Asset 1	Asset 2	Asset 3	return, %
Asset 1	169	10.4	58.5	12.00
Asset 2	10.4	16	6	6.00
Asset 3	58.5	6	225	-7.00

	Optimal *Hedge* Fund portfolio	Optimal *Active* Fund portfolio
Asset 1	13.28 %	33.33 %
Asset 2	95.97 %	66.67 %
Asset 3	-9.25 %	0.00 %
Sum	100.00 %	100.00 %

Expected return, %	8.00	8.00
Standard deviation, %	4.45	5.52

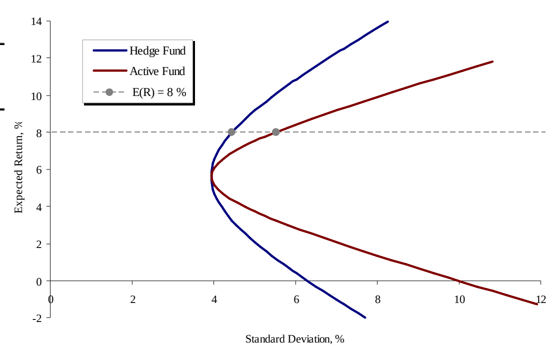

Figure 2.2: Shows how short-selling can improve a portfolios standard deviation without reducing the expected return, if one asset has a negative expected return.

Other reasons why hedge funds might be attractive, is the fact that many of the managers put in a lot of their own money in the fund. This is a signal of confidence, and it ensures that the incentives of the investors and managers are aligned. In addition, the hedge fund industry attracts many of the best fund managers in the world due to their favorable fee structure (often around 20-25% of the upside). Hedge fund managers are also good at only taking risk in fields where they are experts.

2.4. Hedge Fund styles

Hedge funds employ a lot of different investment strategies, and are therefore a very heterogeneous group. It is common for consultants, investors and managers to try to split these funds into more homogeneous group. The only problem is that there does not exist a universal norm for this classification. Different data vendors use different classifications. Alternative Investment Management Association launched a survey in 2003 that showed that the largest outside vendors were Hedge Fund Research and CSFB/Tremont (Lhabitant, 2006). In this thesis the data from Hedge Fund Research (HFR) will be used, and therefore their classification will also be used. They split the hedge fund universe into 37 sub-indices, where the 14 main indices/styles will be described shortly below[9]:

- *Convertible Arbitrage* involves purchasing a portfolio of convertible securities, generally convertible bonds, and hedging a portion of the equity risk by selling short the underlying common stock.
- *Distressed Securities* strategies invest in, and may sell short, the securities of companies where the security's price has been, or is expected to be, affected by a distressed situation. This may involve reorganizations, bankruptcies, distressed sales and other corporate restructurings.
- *Emerging Markets* funds invest in securities of companies or the sovereign debt of developing or "emerging" countries. Investments are primarily long.
- *Equity Hedge* investing consists of a core holding of long equities hedged at all times with short sales of stocks and/or stock index options. Some managers

[9] The definitions are collected from the HFR Internet page (HFR, 2007).

maintain a substantial portion of assets within a hedged structure and commonly employ leverage.

- *Equity Market Neutral* investing seeks to profit by exploiting pricing inefficiencies between related equity securities, neutralizing exposure to market risk by combining long and short positions.
- *Equity Non-Hedge* funds are predominately long equities although they have the ability to hedge with short sales of stocks and/or stock index options. These funds are commonly known as "stock-pickers." Some funds employ leverage to enhance returns. When market conditions warrant, managers may implement a hedge in the portfolio.
- *Event-Driven* is also known as "corporate life cycle" investing. This involves investing in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks.
- *Fixed Income Arbitrage* is a market neutral hedging strategy that seeks to profit by exploiting pricing inefficiencies between related fixed income securities while neutralizing exposure to interest rate risk.
- *Macro* involves investing by making leveraged bets on anticipated price movements of stock markets, interest rates, foreign exchange and physical commodities. Macro managers employ a "top-down" global approach, and may invest in any markets using any instruments to participate in expected market movements.
- *Market Timing* involves allocating assets among investments by switching into investments that appear to be beginning an uptrend, and switching out of investments that appear to be starting a downtrend. This primarily consists of switching between mutual funds and money markets.
- *Merger Arbitrage,* sometimes called Risk Arbitrage, involves investment in event-driven situations such as leveraged buy-outs, mergers and hostile takeovers.
- *Regulation D* managers invest in Regulation D securities, sometimes referred to as structured discount convertibles. The securities are privately offered to the

investment manager by companies in need of timely financing and the terms are negotiated.

- *Relative Value Arbitrage* attempts to take advantage of relative pricing discrepancies between instruments including equities, debt, options and futures. Managers may use mathematical, fundamental, or technical analysis to determine misvaluations.
- *Short Selling* consists of funds that primarily sell securities short.

In addition to the main styles, they also have a Fund of Hedge fund index, FoHF, which is an equal-weighted index of a sample of over 800 FoHF in their database.

2.5. Hedge Funds in Norway and the Nordic countries

As in the rest of the world, the hedge fund industry has also grown enormously in the Nordic countries in the last 6-7 years. Figure 2.3 shows the number of Nordic hedge funds that were reporting figures to HedgeNordic[10] by the end of the year from 1996 to 2006. Figure 2.4 breaks the total number of Nordic hedge funds into country (where the managers operate from) and style. As one can see, Sweden is the county where most of the Nordic hedge funds operate from with just over 50% of all hedge funds. This may be due to regulatory issues, and the fact that Sweden was the first Nordic country to allow hedge funds. The most common hedge fund style is Equities (market share of 47%) which consists of all hedge funds that participate in the equity market. After that comes the Funds of Hedge Funds which has a 27% market share.

Table 2.1 displays the assets under management, AUM, for the Nordic countries at the end of 2006 and the percentage change in 2006. As one can see, Sweden has the largest proportion of AUM with 9.5 billion Euros. After Sweden follows Norway and Denmark with around 1.7-1.8 billion Euros and Finland with just over one billion Euros of AUM.

[10] See www.hedgenordic.com for further details. This database is not a complete list of all hedge funds in the Nordic countries (there exists at least 6 more funds according to an e-mail to HedgeNordic as of January 2007), but it may serve as a proxy.

The total AUM in the Nordic countries sum up to about 14 billion Euros. When it comes to the change in AUM in 2006, the hedge funds in Norway and Finland are the big winners. Their AUM has increased with 107% and 47%, respectively. The more established hedge fund countries, Sweden and Denmark, increased their AUM with around 10-20%. The total increase in AUM in the region was just over 20%.

	AUM	% change
Sweden	9.50	8.8 %
Norway	1.80	107.1 %
Denmank	1.65	17.9 %
Finland	1.10	47.3 %
Total	*14.05*	*20.1 %*

Table 2.1: Total assets under management (billion Euros) as of December 2006 and percentage change from year end 2005[11].

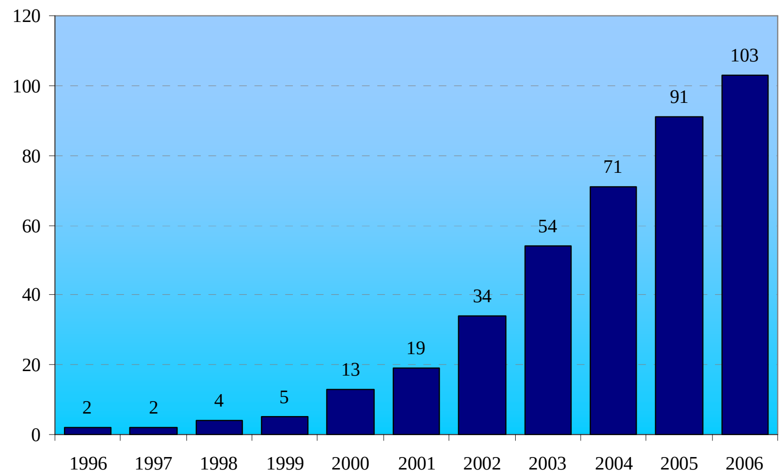

Figure 2.3: Number of Nordic hedge funds in HedgeNordic database as of year end 1996-2006.

[11] The numbers are collected from the April 2007 issue of The Nordic Hedge Fund Journal (page 12).

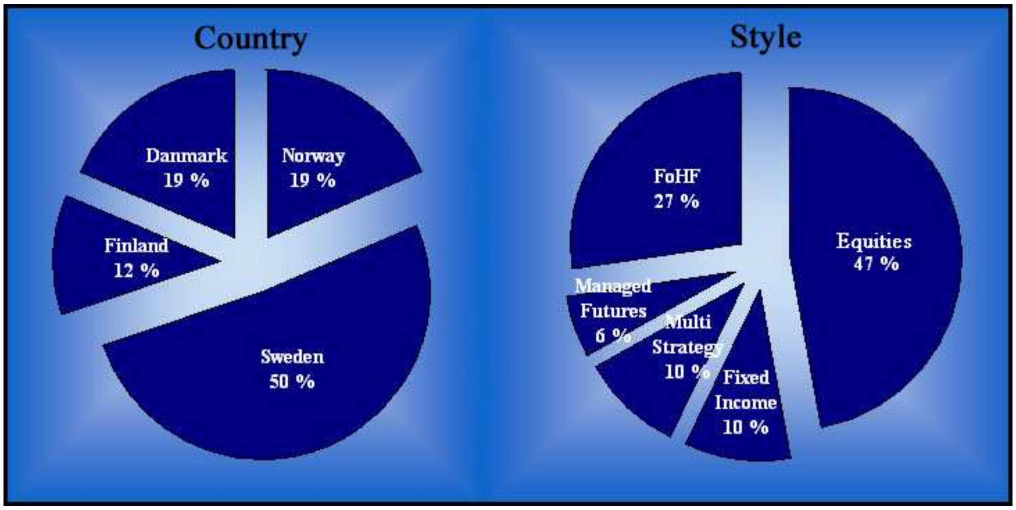

Figure 2.4: Breakdown of Nordic hedge funds into country and style (from HedgeNordic as of January 2007).

The regulation of hedge funds is different among the Nordic countries. Sweden was, as mentioned, the first country to allow hedge funds to be registered and marketed publicly. This happened on 1 April 2004 (Kredittilsynet, 2004). Finland has much the same regulations as Sweden. Any hedge fund must register with the Finnish FSA and must be available to the public[12]. Denmark allows hedge funds to be registered as unions from 1 July 2005 (Aamo, 2006). The unions are open to the public and supervised by *Finanstilsynet*. The minimum equity in the hedge-unions must be DKK 25 millions.

In Norway the case is much different. It is not allowed to register hedge funds as security-funds ("verdipapirfond"), since hedge funds will break many of the rules that are specified for such funds (i.e. short-selling and leveraging). But one can register them as other company forms such as joint-stock company ("aksjeselskap") (Aamo, 2006). None the less, it is more favorable to register funds as security-funds. Aamo (2006) mentions some of the advantages to be:

- Security-funds are better regulated through laws.
- Companies that manage regular funds and depot institutions are supervised by the government.

[12] According to e-mail from HedgeNordic as of 9 February 2007.

- In security-funds the investors are treated equally.
- Security-funds have a better mechanism for subscription and redemption.

The Financial Supervisory Authority of Norway ("Kredittilsynet"), FSA, has on behalf of the Ministry of Finance worked out a proposal for a new law concerning special funds (i.e. hedge funds). This proposal suggests that special funds should be allowed registered in Norway, but only marketed to professional investors[13]. The divisional director at the FSA, Eirik Bunæs, said to The Nordic Hedge Fund Journal[14] in January 2007 that he believes that the Ministry of Finance possibly is adapting a "wait-and-see" attitude while the EU considers its own hedge fund regulation. On the 12 February 2007 Dagens Næringsliv (2007a) wrote that the G7 countries and Russia had met to discuss the hedge fund industry and regulation of it. They were concerned about the risk in the industry and that a possible collapse could seriously hurt the world economy. The conclusion of the meeting was that they were going to continue monitoring the industry and try to open a dialog with it. This indicates that it may take some time before Norway will allow hedge funds to be registered, and it leaves Norway as the only Nordic country that does not allow hedge funds to do so as of today (May 2007). But they can still be managed from Norway as long as they do not market themselves.

[13] Professional investors are defined as investors with at least NOK 5 millions in gross financial wealth and a minimum subscription amount of NOK 500,000.
[14] Journal published by HedgeNordic.com.

3. Traditional Portfolio Theory

In this chapter the traditional portfolio theory will be revisited. First the centralized distributional moments and the mean-variance framework will be described before finally a few traditional asset pricing models and performance measurements will be presented.

3.1. The centralized distribution moments

The centralized distributional moments are the distributional moments less the distribution mean, μ. The n^{th} centralized moment of the stochastic variable, $\tilde{X}$, can then be defined as $E((\tilde{X}-\mu)^n)$. Often only the two first moments are used, but in this thesis the four first moments will be used. The reason for this has to do with the risk in hedge funds which will be thoroughly discussed later. In general, under relatively weak assumptions about the investor's utility function, investors want high uneven moments (mean and skewness) and low even moments (standard deviation and excess kurtosis) (Scott and Horvath, 1980).

3.1.1. Expectation / mean

The first moment of a distribution is the expectation or mean, $E(\tilde{X})$:

$$\mu = E(\tilde{X}) = \sum_{t=1}^{T} p_t X_t \tag{3.1}$$

The centralized first moment is rarely used since it is always zero.

3.1.2. Variance

The second centralized distributional moment is the variance. This is a measure of dispersion around the mean, and is often used in finance to describe the risk of an asset. It is defined as:

$$\sigma^2 = E((\tilde{X} - \mu)^2) = \sum_{t=1}^{T} p_t (X_t - \mu)^2 \tag{3.2}$$

A transformation of the variance that also is used as a measure of dispersion, is the standard deviation, σ, which is the square root of the variance.

3.1.3. Skewness

The third centralized moment is the skewness, and is a measure of the lopsidedness of the distribution. A symmetric distribution (i.e. the normal distribution) will have a centralized third moment of zero. It is defined as:

$$\mu_3 = E((\tilde{X} - \mu)^3) = \sum_{t=1}^{T} p_t (X_t - \mu)^3 \tag{3.3}$$

3.1.4. Kurtosis

The forth centralized moment is the kurtosis which is a measure that tells us if the distribution is fat and short or slim and tall. It is defined as:

$$\mu_4 = E((\tilde{X} - \mu)^4) = \sum_{t=1}^{T} p_t (X_t - \mu)^4 \tag{3.4}$$

The normal distribution has a kurtosis of 3, and it is therefore common to subtract this from the estimated kurtosis. This yields the *excess* kurtosis which is zero for the normal distribution.

3.2. The mean-variance framework

When making investment decisions, investors are interested in the risk-reward relationship. This can be formalized through the mean-variance framework. The framework assumes that the investors are risk averse. That means that they will not take on additional risk if they are not compensated for that with a larger expected return. How large this compensation is depends on the level of risk aversion. A further assumption is that the investor's risk-reward preferences are described by the quadratic utility function. This means that only the two first moments of the return distribution are important to the investor. The returns are therefore indirectly assumed to be normally distributed. This framework may therefore not be the optimal choice if these assumptions are not satisfied.

In theory, the risk and reward in this framework should be expressed as expectations about the future. But it is common to estimate these values based on historical data. This leads to uncertainty or measurement error in the estimates, but they are often thought to be the best measurements we have.

The mean-variance framework was first introduced by Harry Markowitz (1952). His work with risky portfolio selection lead to the *Efficient Frontier* (sometimes called the Markowitz Frontier). This set of portfolios was the best possible portfolios given the individual assets standard deviation and expected return. The shape of the frontier is convex, and the degree of convexity depends on the correlation between the individual assets.

If the universe of risky assets is combined with a risk-free asset, then the *Capital Allocation Line*, CAL, can be drawn. This is a linear line that goes from the risk-free asset through a portfolio of risky assets (assuming that one can both borrow *and* lend at the risk-free rate). If this risky portfolio lies on the efficient frontier, then the CAL is referred to as the *Capital Market Line*, CML (figure 3.1 shows this relationship). The tangency portfolio is then referred to as the market portfolio, and it is the portfolio with the highest possible Sharpe ratio[15]. The expected return of a portfolio *p* on the CML, $E(R_p)$, is then described by equation (3.5).

$$E(R_p) = R_f + \sigma_p \frac{E(R_M) - R_f}{\sigma_M} \tag{3.5}$$

Where R_f is the risk-free rate of return, $E(R_M)$ is the expected return on the market portfolio, and σ_M and σ_p is the standard deviation of the market portfolio and the portfolio *p*, respectively.

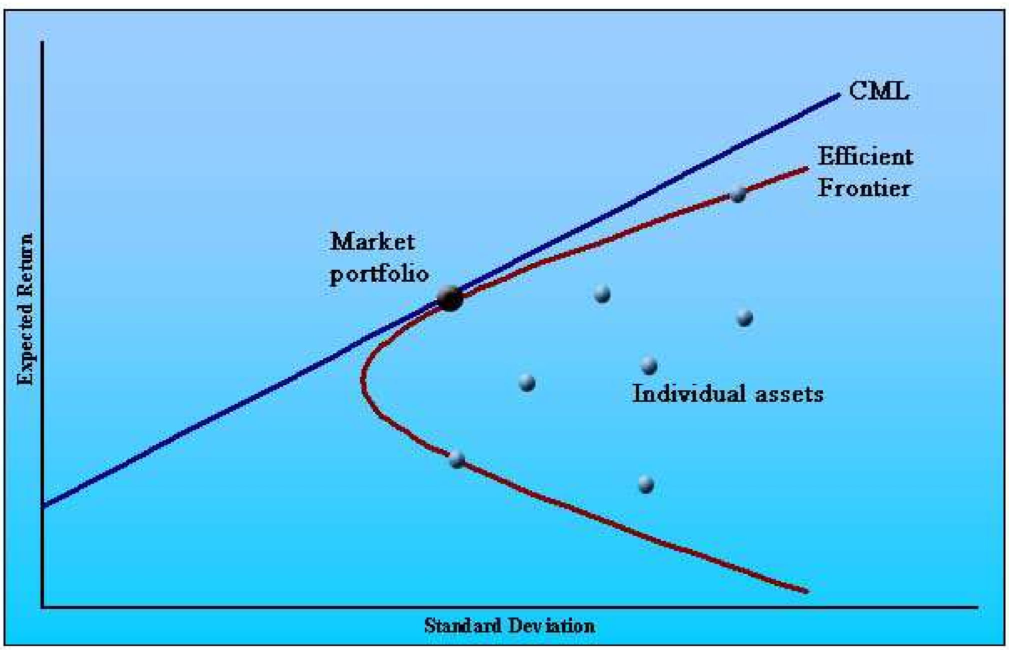

Figure 3.1: Graph that shows the CML, the efficient frontier and the market portfolio.

[15] See chapter 3.4.1.2 for definition of the Sharpe ratio.

3.3. Asset pricing models

3.3.1. The Capital Asset Pricing Model

The CML uses standard deviation as a measure of *total* risk. The standard deviation can be divided into systematic and specific risk. The systematic risk is general risk in the market or economy, while the specific risk is risk associated with individual assets. A well-diversified investor is only expected to get paid for holding systematic risk. Accordingly one can not use the standard deviation to price financial assets.

In the mid 1960's three men independently developed an asset pricing model which is called the Capital Asset Pricing Model, or CAPM. Those men were William Sharpe (1964), John Litner (1965) and the Norwegian Jan Mossin (1966). For this work William Sharpe received the Nobel price in 1990. Their model derives the expected return of an asset from the risk-free rate and the general market risk. Equation (3.6) use the CAPM to derive the expected return for asset *i*, $E(R_i)$.

$$E(R_i) = R_f + \beta_i \left[E(R_M) - R_f \right] \tag{3.6}$$

β_i is a measure of how sensitive asset *i* is to the market, and $E(R_M) - R_f$ is the expected market premium which one can expect to get paid per unit of systematic risk. CAPM should only be interpreted as an *ex-ante* predictive model. The *ex-post* counterpart to CAPM is the empirical Market Model of equation (3.7). The parameters are usually estimated via an Ordinary Least Square, OLS, regression and the coefficients α_i and ε_i should in an efficient market not be statistically different from zero.

$$R_i = \alpha_i + R_f + \beta_i (R_M - R_f) + \varepsilon_i \tag{3.7}$$

The CAPM has received a lot of attention during its years, mostly due to its simplicity and its good theoretical foundation, but has lately been under attack from many researchers worldwide. Even so, it is still used a lot among practitioners.

3.3.2. The Arbitrage Pricing Theory

Another much used pricing model is the *Arbitrage Pricing Theory*, APT. This model was first introduced by Stephen Ross (1976), and it estimates the expected return of an asset as a linear function of several factors, both micro and macro. An assets sensitivity to the factor is measured by the beta coefficient for each factor. The APT is less restricted by assumptions than CAPM, and it can be defined for an unknown number of factors like in equation (3.8).

$$E(R_i) = R_f + \sum_j \beta_j F_j \tag{3.8}$$

3.3.3. The Four Factor Model

One example of a much used APT model is the so-called Four Factor Model of Fama and French (1993) and Jegadeesh and Titman (1993, 2001). This model is derived from research and it consists of Fama and French's Three Factor Model and the momentum effect of Jegadeesh and Titman. Equation (3.9) describes the model.

$$E(R_i) = R_f + \beta_1 \left[E(R_M) - R_f \right] + \beta_2 SMB + \beta_3 HML + \beta_4 UMD \tag{3.9}$$

The SMB (Small Minus Big) factor is supposed to capture the size effect which says that small stocks (measured by their market capitalization) will do better than large stocks. The HML (High Minus Low) factor captures the value effect which says that value stocks (high ratio of book to market value of common equity) will do better than growth stocks (low book to market ratio). The last factor, UMD (Up Minus Down), captures the momentum effect. This effect tells us that past winners will outperform past losers in the short run (3-12 months) (Jegadeesh and Titman, 1993 and 2001). The beta coefficients measure the sensitivity to each factor/effect.

3.4. Absolute performance measurements

In investment it is important to be able to measure a managers or a funds risk-adjusted performance. There have been developed a lot of measures for this purpose. These measures can roughly be divided into two large groups – *absolute* and *relative* performance measurements. The former measures the performance relative to a risk-free asset (i.e. cash) while the latter measures the performance relative to a specified benchmark. Since hedge funds usually do not have a benchmark to be compared to, this thesis will concentrate on the absolute measurements. In section 3.4.1 three traditional measurements will be presented. These depend on the assumption that the returns are normally distributed. That is often not the case (especially for hedge funds) and that has lead to the development of more modern measurements. Five such measurements will be presented in section 3.4.2. In the following, R_i represents the mean return for asset *i* over the sample period, and R_f and R_M are the mean return of the risk-free asset and the market portfolio, respectively. Finally, it is worth noting that all these measures are estimated based on a sample of historical data and will therefore only reflect *past* observed risk and not necessarily *future* risk.

3.4.1. Traditional measurements

3.4.1.1. The Jensen Alpha

According to CAPM, it is impossible for an asset to have a different expected return than what is predicted by the model. If one asset has an expected return that lies below (above) the CAPM predicted return, then investors would rush to sell (buy) the asset which would lead the asset price to fall (rise) and the return to rise (fall) until it is consistent with CAPM. This is how it *should* work, but in reality there may be short term deviations. These deviations can be expressed by the Jensen Alpha, α_i, in equation (3.10).

$$\alpha_i = R_i - E(R_i) \tag{3.10}$$

Equation (3.10) includes the expected return predicted by CAPM, but as mention before this model is an *ex-ante* model. So in order to be able to estimate the Jensen Alpha *ex-post*, the Market Model in equation (3.7) must be used. Rearranging (3.7) yields equation (3.11) which can easily be estimated with an OLS regression. The statistical significance of the Jensen Alpha can then be tested with a standard Student t-statistic (possibly correcting for heteroscedasticity and autocorrelation in the error term).

$$R_i - R_f = \alpha_i + \beta_i (R_M - R_f) + \varepsilon_i \tag{3.11}$$

The Jensen Alpha is a straightforward way of measuring performance, and it is named after Michael Jensen (1968). It is the difference between the realized return and the return predicted by CAPM, and it may therefore be seen as a measure of superior performance if it is positive. If the market had been efficient then the Jensen Alpha should have been zero.

3.4.1.2. The Sharpe ratio

The most commonly used risk-adjusted performance measure is the Sharpe ratio. It is named after William Sharpe (1966), and it measures the excess return per unit of total volatility. Since the ratio uses *total* volatility (the standard deviation) it is best suited for undiversified investors. Algebraically, it is defined as:

$$SR_i = \frac{R_i - R_f}{\sigma_i} \tag{3.12}$$

3.4.1.3. The Treynor ratio

The Treynor ratio is very similar to the Sharpe ratio. The main difference is that it does not focus on the total risk, but instead the *systematic* risk represented by beta. It is therefore a good measure for a well-diversified investor. It is named after Jack L. Treynor (1965), and it can be expressed like this:

$$TR_i = \frac{R_i - R_f}{\beta_i} \tag{3.13}$$

3.4.2. Modern measurements

3.4.2.1. Autocorrelation-adjusted Sharpe ratio

Lo (2002) documents that positive autocorrelation can overestimate the true Sharpe ratio. He therefore recommends using an autocorrelation-adjusted Sharpe ratio which is defined as follows:

$$\text{“AR-adjusted SR}_i\text{”} = SR_i \times \frac{q}{\sqrt{q + 2\sum_{k=1}^{q-1}(q-k)\rho_k}} \tag{3.14}$$

Where SR_i is the regular monthly Sharpe ratio and ρ_k is the kth autocorrelation coefficient. The annualized autocorrelation-adjusted Sharpe ratio is given for q=12. Note that when the return distribution exhibits positive autocorrelation, the fraction in (3.14) will be less than $\sqrt{12}$ (which it would be if the return series was i.i.d.) and the regular Sharpe ratio will be overestimated compared to the true (autocorrelation-adjusted) Sharpe ratio.

3.4.2.2. Modified Sharpe ratio

The autocorrelation-adjusted Sharpe ratio of Lo (2002) only adjusts for autocorrelation in the return distribution. But hedge fund returns often exhibit non-neglectable higher moments as well (skewness and excess kurtosis). Gregoriou and Gueyie (2003) try to account for this through their modified Sharpe ratio which can be defined as follows:

$$\text{“Modified SR}_i\text{”} = \frac{R_i - R_f}{MVaR_i} \qquad (3.15)$$

Where the modified Value-at-risk, $MVaR_i$, is defined as:

$$MVaR_i = \mu_i - \left[z_c + \frac{1}{6}\left(z_c^2 - 1\right)S_i + \frac{1}{24}\left(z_c^3 - 3z_c\right)K_i - \frac{1}{36}\left(2z_c^3 - 5z_c\right)S_i^2 \right] \times \sigma_i \qquad (3.16)$$

Where, μ_i = asset *i*'s drift term (often set to R_i),

z_c = the critical value for probability (1 – α) with a standard normal distribution (-1.96 for 95%),

S_i = the skewness of asset *i*,

K_i = the excess kurtosis of asset *i*, and

σ_i = asset *i*'s standard deviation.

The replacement of the standard deviation in the regular Sharpe ratio with the *MVaR* in the modified Sharpe ratio means that skewness and excess kurtosis are taken into account.

3.4.2.3. The Sortino ratio

The Sortino ratio developed by Sortino and Price (1994) is a performance measurement with focus on downside risk. It replaces the standard deviation in the Sharpe ratio with a downside deviation measurement. This makes the Sortino ratio more appropriate when the returns are left-skewed (which often is the case for hedge funds). Algebraically, it can be defined as:

$$\text{Sortino}_{\text{i}} = \frac{R_i - MAR}{DD_i} \tag{3.17}$$

Where *MAR* (Minimum Acceptable Return) for hedge funds often is set to either zero or equal to the risk-free rate. The downside deviation, *DD*, is estimated as the standard deviation only for those returns in the series that are below the *MAR*. Algebraically, it means that $DD_i = \sqrt{\frac{1}{T}\sum_{t=0}^{T}(R_{it} - MAR)^2}$ *if* $R_{it} < MAR$. The Sortino ratio does not account for excess kurtosis or autocorrelation.

<u>*3.4.2.4. Omega*</u>

The Omega measure was introduced by Keating and Shadwick (2002), and it incorporates *all* the moments of the return distribution. It makes no assumptions on the return distribution or the utility function of the investor. Omega is expressed as the ratio between the gain and loss with respect to a threshold, *L* (equivalent to *MAR* in the Sortino ratio). In continuous time it is defined as:

$$\Omega_i(L) = \frac{\int_L^b (1 - F(R_i))dR_i}{\int_a^L F(R_i)dR_i} \tag{3.18}$$

Where *a* and *b* are the return intervals and $F(R_i)$ is the cumulative distribution of returns below the threshold *L*. De Souza and Gokcan (2004) have rewritten the Omega measure for the discrete case:

$$\Omega_i(L) = \frac{\sum_a^b Max\left(0, R_{it}^{+}\right)}{\sum_a^b Max\left(0, \left|R_{it}^{-}\right|\right)} \tag{3.19}$$

Where R_{it}^{+} (R_{it}^{-}) is the return above (below) the threshold *L* at time *t*.

3.4.2.5. Kappa

The Kappa measure was first introduced by Kaplan and Knowles (2004), and it is a generalized downside risk-adjusted performance measure. The term "generalized" means that it can become any risk-adjusted return measure through a single parameter *n*. It is defined as follows:

$$K_n(\tau)_i = \frac{R_i - \tau}{\sqrt[n]{LPM_n(\tau)_i}} \tag{3.20}$$

Where τ is the investor's minimum acceptable or threshold return (equivalent to *MAR* in the Sortino ratio or *L* in the Omega measure) and $LPM_n(\tau)$ is the n^th^ lower partial moment with respect to the threshold τ. $K_2(\tau)$ equals the Sortino ratio, and $K_1(\tau)+1$ equals the Omega measure. The n^th^ lower partial moment can be defined in two ways (continuous and discrete time, respectively):

$$LPM_n(\tau)_i = \int_{-\infty}^{\tau} (\tau - R_i)^n \, dF(R_i) \tag{3.21}$$

$$LPM_n(\tau)_i = \frac{1}{T}\sum_{t=1}^{T} Max\left(\tau - R_{it}, 0\right)^n \tag{3.22}$$

4. Data Description

In this chapter the data that are used in the thesis will be presented. In addition possible bias in the data sources for hedge funds will be reviewed.

4.1. Data used in this thesis

The main data sources in this thesis are Bloomberg and HedgeNordic[16]. From HedgeNordic the monthly net-of-fee returns for the individual Nordic hedge funds are collected. The access to Bloomberg is obtained through DnB NOR Asset Management. From this database, assets under management (AUM) and the time-series for different MSCI indices are collected. The fund specific data used in chapter 9.3 are collected from both Bloomberg and HedgeNordic.

The time-series returns for the American hedge fund indices are collected from the Hedge Fund Research[17] (HFR) database. These indices are also net-of-fee, and recorded on a monthly basis. Datastream[18] is used to collect all the other necessary data, i.e. different stock and commodity indices and exchange rates. The factors SMB, HML and UMD used in the Four Factor Model are collected from Kenneth R. French's home page[19] and are denoted in US dollars.

In order to better compare the returns from the different Nordic hedge funds (which are noted in local currencies), the time-series returns are transformed into one common currency. The same applies to the broad stock and bond market indices. The choice of this currency has fallen on the US dollar. The reason for this is that it is the most commonly used currency in the financial world, and that the Nordic hedge funds will be

[16] http://www.hedgenordic.com
[17] http://www.hedgefundresearch.com
[18] http://www.thomson.com
[19] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

compared with American ones (which of course are denoted in USD). In addition, all the other factors used are also denoted in USD. Consequently, the conclusions reached in this thesis are most directly applicable for an investor whose base currency is USD. The consequences of this will be discussed in chapter 12. The exchange rates used are the MSCI exchange rates.

When a result in this thesis is referred to as *statistically significant*, it is significant at a 5% level if nothing else is specified[20].

4.2. Possible bias in the data sources

Joining a hedge fund database is a good way to market your hedge fund (especially in Norway where public marketing of hedge funds are not allowed). But this is also done on a voluntary basis, and this means that the databases and their derived hedge fund indices are not necessarily representative for the entire (difficult to observe) hedge fund universe. It is therefore useful to be aware of possible biases in the databases as a consequence of this.

4.2.1. Self-selection bias

While regular mutual funds are required to disclose their performance data to the public, privately organized hedge funds are not. In addition, the hedge fund managers decide themselves what information they choose to provide to the public. This is likely to create a bias, a self-selection bias, because the characteristics and performance of the reporting funds may differ from those who do not report. For example, small funds with a good track record have a strong incentive to report to the database in order to attract new investors. The sample of hedge funds in the databases is therefore not a true random

[20] The analyses are run in Microsoft Excel and the statistical software STATA.

sample of the whole population of funds (which is desired in statistical analyses), so one should account for this when drawing inferences from the sample.

4.2.2. Survivorship bias

The survivorship bias is a frequently discussed bias in previous literature. A cause of the bias is the fact that some funds are excluded from the databases because they no longer exist. This bias may lead the analyses to overstate the historical performance and understate the historical risk. Because of funds that die of poor performance are deleted from the database.

Many databases have started to keep records of dead funds as well. This has made it possible to estimate the survivorship bias. Many studies have been conducted on this topic, and the annual estimated biases (on average return) range from 0.16% in Ackermann, McEnally and Ravenscraft (1999) to 3.4% in Fung and Hsieh (1997b) depending on the databases and sample period.

The database for Nordic hedge funds at HedgeNordic includes dead funds, and they are also included in this thesis. This reduces (if not eliminates) the survivorship bias for Nordic hedge funds.

4.2.3. Backfill bias

This bias occurs when funds that are joining a database are allowed to backfill their performance data. The funds therefore get an instant history even though they were not part of the database in previous years. Some databases, like HFR, do not allow firms to backfill their performance history. This eliminates the bias.

Some studies have also tried to estimate this type of bias (Fung and Hsieh (2000, 2001) and Barry (2003)). The annual estimated biases (on average return) range from 1.2-1.4%.

4.2.4. Database/sample selection bias

The selection of a database and/or sample of hedge funds for analysis may also create a performance bias. The databases are different from each other. Funds usually only report to one or two databases, but rarely to all. This bias applies mostly to the American databases (like HFR). For Nordic hedge funds there does not exist many databases, and this thesis include all funds in the HedgeNordic database (i.e. not a sample from the database). This bias may therefore not be that severe for this thesis.

4.2.5. Infrequent pricing and illiquidity bias

One final bias that may influence the results is the fact that hedge fund managers have the ability and tendency to “manage” their monthly net asset value in order to smooth their returns. This is according to Lhabitant (2006) particularly a problem for hedge funds that hold illiquid or difficult to price over-the-counter securities (i.e. small cap stocks, emerging market bonds or distressed assets), and for US onshore limited partnerships since many of them value their own portfolio. This may create autocorrelation in the hedge fund returns. Analyses of the autocorrelation will be conducted in chapter 5 and in chapter 8.2 the CAPM will be adjusted for this possible bias.

5. Descriptive Statistics for Hedge Funds

In this first empirical chapter the descriptive statistics of individual Nordic hedge fund returns will be briefly presented and discussed. In addition, they will be compared to a sample of American hedge fund indices as well as some general stock and bond indices.

5.1. Previous studies

There have been conducted numerous international studies on the descriptive statistics and performance of hedge funds. Most of them focus on American hedge funds. Few, if any, have focused on Nordic hedge funds.

Brooks and Kat (2002) use a sample of 48 different American hedge fund indices (from different databases) over the period from January 1995 to April 2001 to examine the statistical properties. They find that most of the indices have relatively high mean return and relatively low standard deviation compared to stocks and bonds. This would be a clear violation of the market efficiency hypothesis if it had not been for the fact that their hedge fund indices also exhibit a relatively low skewness (i.e. negative) and high excess kurtosis compared to stocks and bonds. That means that for hedge fund indices, large negative returns are relatively more likely to occur than for stocks or bonds. Their sample also shows a significant positive autocorrelation in the hedge fund indices. This was not the case for the stock and bond indices which have little autocorrelation. Finally, they found that fund of hedge funds, FoHF's, had a lower mean return than the average hedge fund. This suggests that FoHF's does not add enough value to make up for the fees they charge.

Kat and Lu (2002) examine the statistical properties of 376 individual American hedge funds and 103 FoHF's in the period from June 1994 to May 2001 (from the CSFB/Tremont database). They look at fund properties from two different angles. Firstly, they calculate the cross-sectional average statistical properties for all individual funds within a style. Doing this they get pretty much the same results as Brooks and Kat (2002), with low skewness (i.e. negative), high excess kurtosis and high positive first-order autocorrelation. Secondly, they calculate the properties for equally-weighted style-portfolios. Then they get a substantial reduction in the standard deviations, which signal low correlations and diversification benefits within funds of the same style. The skewness, on the other hand, is not diversified away when portfolios are formed. In fact it becomes more negative. It appears that when one fund does poorly, other funds in the same sector does poorly as well. For most of the portfolio the excess kurtosis decreases and the positive first-order autocorrelation increases. Like Brooks and Kat (2002) they also find that FoHF's produces a lower mean return than the aggregate hedge fund index.

Frydenberg et. al. (2006) look at the 13 CSFB/Tremont asset-weighted indices over the period from January 1994 to June 2005. Their results were very much in line with the previous studies. The indices often exhibit low skewness and high excess kurtosis in addition to high autocorrelation.

5.2. Nordic Hedge Funds

Like Kat and Lu (2002), the statistical properties of Nordic hedge funds are analyzed in two different ways. The first approach (panel A of table 5.1) estimates the properties as the cross-sectional average of all the individual funds' properties, while the second approach (panel B of table 5.1) estimates the properties of an equally-weighted style index.

	MONTHLY RETURNS						
A: Individual funds	Mean	St.dev.	Skewness	Ex. kurtosis	AR(1), %	AR(1-3), %	Normality, %
Equities	1.47	3.61	0.21	-2.73	10.20 %	8.16 %	20.41 %
Fixed Income	0.98	3.11	0.03	-3.34	10.00 %	10.00 %	20.00 %
Multi Strategy	1.11	2.90	0.18	-2.97	15.38 %	7.69 %	15.38 %
Managed Futures	1.19	5.36	0.47	-2.70	33.33 %	0.00 %	16.67 %
Fund of Funds	0.79	2.72	0.39	-2.55	0.00 %	10.34 %	13.79 %
Total	1.18	3.33	0.25	-2.76	9.35 %	8.41 %	17.76 %
B: Indices	Mean	St.dev.	Skewness	Ex. kurtosis	AR(1)	Q(3)	Jarque-Bera
Equities	2.02	4.21	0.40	-1.74	**0.28**	**11.82**	**19.16**
Fixed Income	1.19	3.35	0.07	-3.48	-0.03	3.13	**34.90**
Multi Strategy	1.12	2.94	0.07	-3.15	0.01	3.43	**44.78**
Managed Futures	1.62	4.71	0.60	-2.99	**0.25**	**7.89**	**34.49**
Fund of Funds	1.03	2.90	0.91	1.84	0.09	3.06	**35.14**
Composite	1.45	2.72	0.32	-3.52	0.10	1.59	**67.39**

Table 5.1: Statistical properties of the return series for Nordic hedge funds in the period from July 1996 to December 2006. AR(1) in panel A shows the percentage of individual funds which has a significant AR(1) coefficient, AR(1-3) shows the percentage of funds with significant Q(3)-statistic, and the last column shows the percentage of funds with normally distributed returns. The three last columns in panel B show the AR(1), Q(3) and Jarque-Bera coefficients for the style indices. Bold numbers indicate significance.

Overall, one can see that all the means are positive. The means in both approaches should have been the same if all the funds had been alive for the entire sample period. But this is not the case, and that’s the reason for the deviations in the means (within the styles). Equities have the highest mean, while FoHF’s have the lowest. That is also what one would expect considering the investment nature of the styles. The standard deviations are all relatively low, perhaps with exception of Equities and Managed Futures.

It is interesting to notice the risk/return-relationship between FoHF’s and the composite index in panel B of table 5.1. FoHF’s have a much lower mean return and a higher standard deviation than the composite index. The annualized Sharpe-ratios[21] (0.87 for FoHF’s and 1.45 for the composite index) show that a diversified portfolio of all hedge funds have performed better than the average FoHF. This may indicate that the FoHF managers do not add enough value to justify the fees that they charge. This interesting fact is also true for panel A.

[21] See appendix 1.

When it comes to skewness and excess kurtosis, the picture is different from previous studies. The average individual skewness' are all positive, which is not in line with previous studies. All the individual excess kurtoses and most of the index kurtoses are negative. Again, this is not in line with previous studies.

Previous studies have also found significant autocorrelation in hedge fund returns. That is also the case for some of the Nordic funds. Multi Strategy and Managed Futures are the two styles with the most significant individual autocorrelation with about 15% and 33%, respectively, of all individual funds. In addition both the Equities and Managed Futures indices (panel B) have significant first-order autocorrelations of 0.28 and 0.25, respectively. The composite index does not have a significant first-order autocorrelation.

A Ljung-Box (1978) test for the null hypothesis that all of the first three autocorrelation coefficients are jointly zero is also presented in table 5.1. This Q-statistic shows that two indices have to reject this null. For both Equities and Managed Futures only the first autocorrelation coefficient out of the first three are significantly different from zero, but that is enough to reject the Ljung-Box null.

Finally, a Jarque-Bera (1987) test for normality in the returns is presented in table 5.1. This statistic rejects all the null hypotheses that the return distributions for the indices are normally distributed. The range of individual funds with normally distributed returns is 14-20%. These results do not come as a surprise. It has more or less become an established fact in academia that stock returns usually are not normally distributed, and this especially holds for hedge fund returns with unusual third and fourth moments.

Table 5.2 presents the same statistics as in table 5.1, but now for a selection of stock and bond indices. The means and standard deviations are approximately what one would expect, perhaps with the exception that the mean bond returns seem a bit low. Almost all indices exhibit negative skewness which is lower than for hedge funds. This favors hedge funds. Also all the excess kurtoses are negative, and they are much the same as for hedge funds (except for the FoHF index which has a positive excess kurtosis). Only the

Handelsbanken Nordic index exhibits a significant first-order autocorrelation coefficient, while none of the indices can reject the null hypothesis that all the first three autocorrelation coefficients are zero. This is somewhat different from hedge funds where there is slightly more indications of autocorrelation (especially for American funds). Like the hedge funds, all of the stock and bond indices can reject the null that the returns are normally distributed. Again, this is not surprising.

	MONTHLY RETURNS						
	Mean	St.dev.	Skewness	Ex. kurtosis	AR(1)	Q(3)	Jarque-Bera
Bonds:							
Lehman Global	-0.01	0.85	-0.54	-2.80	0.09	3.52	**47.48**
Lehman US Government	-0.01	1.25	-0.69	-1.85	0.00	4.64	**27.88**
Handelsbanken Nordic	-0.02	2.58	0.46	-2.23	**0.16**	3.93	**30.65**
Equities:							
MSCI World	0.51	4.15	-0.78	-2.03	0.04	0.92	**34.39**
MSCI US	0.59	4.47	-0.61	-2.39	-0.01	0.85	**37.80**
MSCI Nordic	1.02	6.98	-0.40	-2.31	0.12	3.38	**31.31**

Table 5.2: Statistical properties of the return series for a selection of stock and bond indices in the period from July 1996 to December 2006. Bold numbers indicate significance.

5.3. American Hedge Funds

In table 5.3 the same statistical properties as in the previous two tables are presented for a sample of American hedge fund indices from the HFR database.

The means and standard deviations are somewhat lower than for Nordic hedge funds, with one exception when it comes to the standard deviations. The Short Selling index has a larger standard deviation than all the other hedge fund indices (both Nordic and American). This index also has the lowest mean.

The skewness of the indices varies a lot, but around half of them are in the order of -1 and below. This is substantially lower than for Nordic hedge funds. Those indices with positive skewness are almost in the same order as for the Nordic hedge funds. Half of the excess kurtoses are above zero and a few of them are also very high. This is again different from the Nordic hedge funds, but in line with the other international studies.

All of the indices exhibit positive first-order autocorrelation and the majority of them are significantly different from zero as well. Just above half of them also have a significant Q-statistic, meaning that at least one of the first three autocorrelation coefficients are different form zero. Like Brooks and Kat (2002), the two indices with the highest first-order autocorrelation coefficients are Convertible Arbitrage and Distressed Securities. Their explanation for this lies in the "difficulty for hedge fund managers to obtain up-to-date valuations for their positions in illiquid and complex over-the-counter securities" (Brooks and Kat, 2002). It looks like the American hedge fund indices exhibit more autocorrelation than their Nordic counterparts.

As for the Nordic hedge funds, almost all of the American indices do not have normally distributed returns according to the Jarque-Bera statistics. Some of them are even far from being so, and that is mostly due to a very high excess kurtosis.

Compared to the stock and bond indices in table 5.2, the risk/return-relationship (measured by the annualized Sharpe-ratio) is much better for most of the American hedge fund indices if one only takes the mean and standard deviation into account. The only exception is the Short Selling index which does very poorly. The American hedge fund indices also exhibit more dispersion in the skewness and excess kurtosis numbers with many being positive as well. In addition they are more exposed to autocorrelation in the returns in contrast to the stock and bond indices.

	MONTHLY RETURNS						
	Mean	St.dev.	Skewness	Ex. kurtosis	AR(1)	Q(3)	Jarque-Bera
HFRI Convertible Arbitrage Index	0.75	0.98	-0.90	-0.67	**0.49**	**36.73**	**19.35**
HFRI Distressed Securities Index	0.96	1.58	-1.71	6.66	**0.42**	**24.01**	**293.85**
HFRI Emerging Markets (Total)	1.05	4.24	-1.09	2.49	**0.30**	**12.92**	**57.44**
HFRI Equity Hedge Index	1.07	2.65	0.37	-0.97	**0.16**	4.09	**7.77**
HFRI Equity Market Neutral Index	0.60	0.88	0.44	-1.87	0.00	0.81	**22.37**
HFRI Equity Non-Hedge Index	1.02	4.19	-0.44	-2.54	0.13	3.96	**37.79**
HFRI Event-Driven Index	1.00	1.87	-1.36	2.60	**0.26**	**9.03**	**74.35**
HFRI Fixed Income (Total)	0.63	0.90	-1.26	1.81	**0.29**	**14.45**	**50.45**
HFRI Macro Index	0.81	1.88	0.47	-2.15	0.05	0.86	**28.80**
HFRI Market Timing Index	1.01	2.16	0.07	-3.61	0.01	1.23	**68.43**
HFRI Merger Arbitrage Index	0.74	1.09	-2.00	6.01	**0.23**	**11.67**	**273.88**
HFRI Regulation D Index	1.12	2.04	0.73	-0.74	**0.33**	**21.74**	**14.07**
HFRI Relative Value Arbitrage Index	0.76	0.91	-2.84	17.05	**0.29**	**15.94**	**1694.94**
HFRI Short Selling Index	0.31	6.06	0.27	-0.33	0.07	2.29	2.13
HFRI Fund of Funds Composite Index	0.66	1.71	-0.27	1.57	**0.32**	**15.05**	**14.53**
HFRI Fund Weighted Composite Index	0.88	2.09	-0.46	0.13	**0.18**	4.82	4.45

Table 5.3: Statistical properties of the return series for a sample of American hedge fund indices in the period from July 1996 to December 2006. Bold numbers indicate significance.

6. Diversification Benefits from Hedge Funds

In the previous chapter it was established that hedge funds had a relatively good risk/return relationship compared to stocks and bonds. This is one of the advantages with hedge funds. Another advantage is the diversification benefits which will be examined in this chapter. The correlation coefficients between hedge funds (both Nordic and American) and stock and bond indices will be calculated for different market environments. In addition the optimal number of hedge funds in a portfolio will be estimated based on the correlation between individual Nordic hedge funds.

6.1. Previous studies

Denver and Hutson (2006) uses 332 FoHF's over the period from 1990 to 2003 to examine their correlation to stock and bond indices. They find that hedge funds in general exhibit relatively low correlation to stock indices, and that FoHF's have a lower correlation than the hedge fund indices. For bond indices both FoHF's and hedge fund indices have a relatively low correlation. They also find some evidence of asymmetric correlation. Hedge funds have a relatively large correlation with stocks in bear markets, in contrast to bull markets.

Kat and Lu (2002) find that individual hedge funds generally have a low correlation with stock indices, but that this varies a lot between the styles. The correlation with bond indices tends to be closer to zero and vary inversely with the correlation with stocks. When they combine the individual hedge funds into equally-weighted portfolios, the correlation with both bonds and stocks increases. It looks like portfolios tend to follow the general stock and bond market more closely than individual funds. Finally, they find that the correlations between individual hedge funds are quite low. This may indicate that there are major diversification benefits from combining individual funds into portfolios.

Brooks and Kat (2002) find that most of the hedge fund indices exhibit low and typically negative correlation with bonds, and a surprisingly high correlation with stocks. These results are supported by Fung and Hsieh (2002), which in addition find that the correlation is in general lower for individual funds. This lead them to believe that by increasing the number of hedge funds in a portfolio, the idiosyncratic, fund specific risk was replaced by systematic market risk.

Caglayan and Edwards (2001a) study the asymmetric correlation for hedge funds in the period from 1990 to 1998. Like Denver and Hutson (2006) they find that the correlation between hedge funds and the stock market increases in bear markets and decreases in bull markets.

Like Kat and Lu (2002), Anjilvel et. al. (2001) find that the average correlation between individual hedge funds is quite low. They also run a simulation to find out how many hedge funds that are needed to capture the majority of the diversification benefits. If one combines funds from all styles, 15-20 hedge funds are needed.

6.2. Correlations with the stock and bond market

6.2.1. In general

Table 6.1 shows the correlation coefficients between Nordic hedge funds and 6 different stock and bond indices for the whole sample period (July 1996 – December 2006). The stock market is represented by three MSCI indices (World, US and Nordic), while the bond market is represented by Lehman Global Aggregate (broad-based measure of the global investment grade debt market), Lehman US Aggregate Government (non-securitized component of the Lehman US Aggregate index), and the Handelsbanken Nordic (equally-weighted portfolio of country specific bond indices). As in chapter 5 the table is divided into two panels. Panel A measures the correlation to the stock and bond market for equally-weighted style indices, while panel B measures the individual cross-sectional average correlation to the stock and bond market.

The correlation between Nordic hedge funds and the stock and bond market in table 6.1 is generally low (with a few exceptions). This is very good for diversification benefits. The *total* average individual correlation to the stock market is around 0.22-0.39 while the correlation to the bond market is closer to zero. The average individual correlations with stocks are mostly higher than for the indices, especially for Fixed Income and Managed Futures. For bonds this is not the case. Then the index correlations are mostly higher than the average individual correlations, especially for Fixed Income and Managed Futures. This indicates that creating portfolios of individual hedge funds decreases the exposure to stocks but increases the exposure to bonds. One final, very interesting observation in table 6.1 is the relatively high correlation for all styles to the two Nordic indices – MSCI Nordic and Handelsbanken Nordic. This may indicate that the Nordic hedge funds are more exposed to the Nordic stock and bond markets than to other markets around the world. This exposure will be further examined in chapter 9.2.

A: Indices	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	0.24	0.15	0.38	0.08	0.08	0.36
Fixed Income	0.10	-0.01	0.19	0.39	0.37	0.80
Multi Strategy	0.30	0.21	0.37	0.22	0.21	0.71
Managed Futures	0.01	-0.11	0.08	0.43	0.42	0.78
FoHF	0.42	0.37	0.46	0.15	0.13	0.18
Composite	0.32	0.24	0.44	0.24	0.23	0.55

B: Individual funds	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	0.35	0.23	0.39	0.06	0.07	0.27
Fixed Income	0.24	0.12	0.26	0.26	0.25	0.48
Multi Strategy	0.34	0.22	0.39	0.08	0.07	0.37
Managed Futures	0.31	0.19	0.32	0.12	0.10	0.37
FoHF	0.42	0.25	0.45	0.06	0.05	0.23
Total	0.35	0.22	0.39	0.08	0.08	0.29

Table 6.1: Correlation coefficients between the different Nordic hedge fund styles and 6 different stock and bond indices for the whole sample period.

Table 6.2 shows the same correlation coefficients as in panel A of table 6.1, but now for American hedge fund indices. Overall the indices exhibit higher correlations with the stock market than the Nordic hedge funds do. The only three styles with relatively low correlation to stocks are Convertible Arbitrage, Equity Market Neutral and Short Selling (negative). The correlation to the bond market is overall relatively low.

	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
HFRI Convertible Arbitrage Index	0.25	0.24	0.22	0.01	-0.02	-0.07
HFRI Distressed Securities Index	0.52	0.45	0.43	-0.09	-0.13	-0.02
HFRI Emerging Markets (Total)	0.68	0.61	0.61	-0.16	-0.20	-0.11
HFRI Equity Hedge Index	0.74	0.69	0.72	-0.10	-0.12	-0.03
HFRI Equity Market Neutral Index	0.15	0.12	0.16	0.04	0.15	-0.02
HFRI Equity Non-Hedge Index	0.83	0.79	0.75	-0.12	-0.17	-0.01
HFRI Event-Driven Index	0.72	0.66	0.64	-0.12	-0.18	-0.05
HFRI Fixed Income (Total)	0.44	0.39	0.41	0.09	0.02	0.03
HFRI Macro Index	0.44	0.38	0.45	0.18	0.16	0.14
HFRI Market Timing Index	0.72	0.67	0.71	-0.03	-0.05	0.00
HFRI Merger Arbitrage Index	0.53	0.49	0.49	-0.09	-0.11	-0.07
HFRI Regulation D Index	0.33	0.32	0.39	-0.12	-0.11	-0.11
HFRI Relative Value Arbitrage Index	0.47	0.46	0.39	-0.02	-0.04	-0.10
HFRI Short Selling Index	-0.73	-0.70	-0.68	0.15	0.16	0.00
HFRI Fund of Funds Composite Index	0.61	0.55	0.62	-0.05	-0.08	-0.09
HFRI Fund Weighted Composite Index	0.77	0.72	0.73	-0.10	-0.13	-0.04

Table 6.2: Correlation coefficients between American hedge fund styles and 6 different stock and bond indices for the whole sample period.

6.2.2. In bull market

Table 6.3 shows the same correlations as table 6.1, but now only when the Nordic stock market is bull. The definition used for a bull market is when the MSCI Nordic index has a positive monthly return, which consists of around 60% of all months in the sample.

Overall the correlations with the stock market are mostly lower in a bull market than for the whole sample period. The correlation with the bond market is slightly higher in a bull market with the exception for the Handelsbanken Nordic index. The correlations to the stock market are generally higher for the average individual fund than for the indices, while the opposite is true for the correlations with the bond market. Portfolios of hedge funds in bull markets decrease the exposure to stocks slightly and increase the exposure significantly to bonds.

A: Indices	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	0.12	0.06	0.25	0.09	0.11	0.27
Fixed Income	0.11	-0.06	0.08	0.46	0.46	0.78
Multi Strategy	0.06	-0.04	0.11	0.22	0.22	0.65
Managed Futures	0.07	-0.14	-0.02	0.53	0.54	0.81
FoHF	0.20	0.14	0.38	0.26	0.24	0.13
Composite	0.17	0.10	0.27	0.29	0.28	0.47
B: Individual funds	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	0.29	0.06	0.33	0.07	0.09	0.24
Fixed Income	0.25	0.00	0.20	0.32	0.30	0.48
Multi Strategy	0.25	0.02	0.29	0.03	0.02	0.31
Managed Futures	0.30	0.07	0.28	0.16	0.14	0.37
FoHF	0.31	-0.01	0.33	0.05	0.07	0.18
Total	0.29	0.03	0.31	0.09	0.10	0.26

Table 6.3: Correlation coefficients between the different Nordic hedge fund styles and 6 different stock and bond indices during bull stock markets.

Table 6.4 shows the correlations for American hedge fund indices in a bull market. Now the definition of a bull market is when the MSCI US index has a positive monthly return. Most of the correlations between the hedge fund indices and the stock indices decrease in bull markets, while there is little change in the correlations to the bond market.

	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
HFRI Convertible Arbitrage Index	0.32	0.29	0.20	0.14	0.10	-0.07
HFRI Distressed Securities Index	0.18	-0.04	0.23	-0.04	-0.09	-0.07
HFRI Emerging Markets (Total)	0.34	0.15	0.40	-0.19	-0.24	-0.22
HFRI Equity Hedge Index	0.48	0.38	0.47	-0.11	-0.09	-0.05
HFRI Equity Market Neutral Index	0.08	0.11	0.10	-0.02	0.15	-0.13
HFRI Equity Non-Hedge Index	0.59	0.45	0.51	-0.14	-0.15	0.00
HFRI Event-Driven Index	0.38	0.20	0.38	-0.06	-0.10	0.00
HFRI Fixed Income (Total)	0.00	-0.08	0.18	0.17	0.11	-0.04
HFRI Macro Index	0.21	0.13	0.28	0.11	0.09	-0.04
HFRI Market Timing Index	0.59	0.42	0.50	-0.17	-0.15	-0.04
HFRI Merger Arbitrage Index	0.22	0.14	0.12	0.10	0.12	0.05
HFRI Regulation D Index	0.22	0.22	0.21	-0.04	0.02	-0.12
HFRI Relative Value Arbitrage Index	0.19	0.15	0.09	0.11	0.14	-0.10
HFRI Short Selling Index	-0.53	-0.45	-0.46	0.18	0.19	0.03
HFRI Fund of Funds Composite Index	0.25	0.14	0.41	-0.04	-0.05	-0.21
HFRI Fund Weighted Composite Index	0.49	0.35	0.50	-0.10	-0.10	-0.09

Table 6.4: Correlation coefficients between American hedge fund styles and 6 different stock and bond indices during bull stock markets.

6.2.3. In bear market

Table 6.5 shows the correlations between Nordic hedge funds and stock and bond indices during a Nordic bear stock market. The definition of a bear market is when the MSCI Nordic index has a negative monthly return.

In bear markets the correlations (both for individual funds and the indices) to the stock market decrease substantially compared to the whole sample period, and even become slightly negative for some styles. This is very good news for the Nordic hedge funds, as it is a good thing to be little correlated to a bear market. This is not in line with previous studies for American hedge funds. When it comes to bonds the correlations with individual funds mostly increase.

The correlations with stocks are roughly in the same ballpark, or perhaps slightly higher, for hedge fund indices than for the average individual hedge funds. The correlations with bonds are on average higher for indices. In bear markets the creation of portfolios will increase the exposure to stocks slightly and significantly to bonds.

A: Indices	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	-0.20	-0.28	0.00	0.18	0.26	0.50
Fixed Income	-0.22	-0.36	0.17	0.35	0.33	0.84
Multi Strategy	0.14	0.09	0.27	0.38	0.40	0.81
Managed Futures	-0.28	-0.39	-0.07	0.37	0.35	0.74
FoHF	0.35	0.32	0.24	0.10	0.15	0.18
Composite	-0.01	-0.07	0.10	0.35	0.41	0.72
B: Individual funds	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	-0.08	-0.13	-0.03	0.10	0.13	0.30
Fixed Income	-0.12	-0.13	-0.04	0.00	0.08	0.31
Multi Strategy	0.02	-0.10	0.14	0.28	0.30	0.39
Managed Futures	0.26	0.24	0.24	0.16	0.18	0.36
FoHF	0.01	-0.05	0.01	0.13	0.13	0.24
Total	-0.03	-0.08	0.02	0.12	0.15	0.30

Table 6.5: Correlation coefficients between the different Nordic hedge fund styles and 6 different stock and bond indices during bear stock markets.

Table 6.6 shows the correlations for American hedge fund indices in a bear market. The definition of a bear market is when the MSCI US index has a negative monthly return. As for the correlations in a bull market (table 6.4) the correlations between the hedge fund indices and the stock indices in a bear market decreases mostly. But the decrease is not as large as in a bull market. This means that the hedge fund indices tend to follow the stock market more in a bear market than in a bull market, and that is not good news for American hedge fund indices. A slight majority of the correlations with the bond market also decrease in a bear market.

	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
HFRI Convertible Arbitrage Index	0.16	0.15	0.15	-0.14	-0.14	-0.05
HFRI Distressed Securities Index	0.51	0.51	0.30	-0.14	-0.10	0.09
HFRI Emerging Markets (Total)	0.66	0.58	0.45	-0.14	-0.08	0.07
HFRI Equity Hedge Index	0.61	0.51	0.63	-0.09	-0.02	0.11
HFRI Equity Market Neutral Index	0.16	0.06	0.18	0.14	0.17	0.12
HFRI Equity Non-Hedge Index	0.69	0.62	0.62	-0.15	-0.10	0.13
HFRI Event-Driven Index	0.64	0.59	0.48	-0.20	-0.19	0.01
HFRI Fixed Income (Total)	0.61	0.52	0.37	0.01	-0.02	0.23
HFRI Macro Index	0.33	0.19	0.34	0.36	0.43	0.49
HFRI Market Timing Index	0.35	0.22	0.52	0.21	0.29	0.22
HFRI Merger Arbitrage Index	0.51	0.47	0.51	-0.24	-0.23	-0.10
HFRI Regulation D Index	0.17	0.14	0.35	-0.22	-0.18	-0.06
HFRI Relative Value Arbitrage Index	0.40	0.42	0.33	-0.13	-0.13	-0.06
HFRI Short Selling Index	-0.53	-0.48	-0.52	0.16	0.04	-0.14
HFRI Fund of Funds Composite Index	0.59	0.48	0.53	-0.05	0.01	0.12
HFRI Fund Weighted Composite Index	0.68	0.59	0.61	-0.11	-0.05	0.11

Table 6.6: Correlation coefficients between American hedge fund styles and 6 different stock and bond indices during bear stock markets.

6.2.4. During financial crises

Hedge funds are said to be supposed to protect stock portfolios against downside risk due to their low correlation with stocks. This seems to work reasonable well in regular bear markets, but what happens when the overall financial markets are suffering from a major financial crisis? Table 6.7 estimates the correlations coefficients between Nordic hedge funds and the stock and bond market during 4 major international financial crises. These crises are (months used in the estimation are presented in parenthesis):

- The Asian crisis in 1997 (May – December).
- The Russian crisis in 1998 (May – December).
- The burst of the Dot Com bubble in 2000 (March – December).

- The September 11th terror attack in 2001 (September – November).

This sample is relatively small, consisting of only 29 months and 17 individual hedge funds. This may lead to somewhat spurious results, which must be interpreted with caution.

During financial crises the correlations between individual hedge funds and the stock market are mostly negative except for Multi Strategy and FoHF. The latter has a very high positive correlation which is not good, but this estimate is only based on three hedge funds so the result may be subject to some uncertainty. For indices, on the other hand, the correlation to the stock market is mostly positive except for Fixed Income and Managed Futures. Again FoHF's have a relatively high positive correlation. The correlation between Nordic hedge funds (both individual and indices) and the bond market is mostly positive during financial crises, perhaps with the exception of FoHF's and Equities. It is also very high (and positive) for Fixed Income and Managed Futures. All in all, it may seem like it is an advantage to keep (the average) individual hedge funds in stead of well diversified portfolios of hedge funds during a financial crisis (since individual correlations are mostly negative and FoHF does so poorly). These results should be viewed with some caution due to a small sample of funds and observations per fund. The correlation coefficient between the Fixed Income index and the Lehman US Government index is only *approximately* equal to 1, not exactly 1 (rounding error).

A: Indices	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	0.12	-0.01	0.26	-0.11	-0.08	0.33
Fixed Income	-0.67	-0.77	-0.41	0.96	1.00	0.99
Multi Strategy	0.15	0.10	0.24	0.31	0.34	0.73
Managed Futures	-0.21	-0.37	0.13	0.54	0.56	0.96
FoHF	0.60	0.61	0.51	0.10	0.08	-0.07
Composite	0.27	0.20	0.36	0.27	0.27	0.55
B: Individual funds	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
Equities	-0.26	-0.32	-0.25	0.29	0.41	0.56
Fixed Income	-0.58	-0.69	-0.33	0.92	0.95	0.94
Multi Strategy	0.23	0.15	0.36	0.27	0.33	0.73
Managed Futures	-0.29	-0.43	0.01	0.78	0.77	0.93
FoHF	0.70	0.71	0.52	-0.08	-0.07	-0.14
Total	-0.11	-0.18	-0.04	0.37	0.44	0.59

Table 6.7: Correlation coefficients between the different Nordic hedge fund styles and 6 different stock and bond indices during major financial crises.

Table 6.8 shows the same correlations as table 6.7, but only for American hedge fund indices. The correlations with the stock market are on average very high which indicates that if a major financial crisis occurs, many hedge funds will also do poorly. The only exception is the Short Selling index, which of course is highly negatively correlated as it makes money when the stock market drops. The correlation with the bond market also increases a bit for most of the hedge fund indices, but they are still close to zero.

	MSCI World	MSCI US	MSCI Nordic	Lehman Global	Lehman US Gov.	Handelsbanken Nordic
HFRI Convertible Arbitrage Index	0.46	0.46	0.43	-0.20	-0.20	-0.30
HFRI Distressed Securities Index	0.65	0.62	0.67	-0.22	-0.20	-0.18
HFRI Emerging Markets (Total)	0.80	0.75	0.75	-0.13	-0.17	-0.06
HFRI Equity Hedge Index	0.82	0.80	0.70	0.00	0.04	0.14
HFRI Equity Market Neutral Index	0.29	0.31	0.29	0.05	0.19	-0.04
HFRI Equity Non-Hedge Index	0.87	0.85	0.75	-0.08	-0.04	0.07
HFRI Event-Driven Index	0.81	0.76	0.77	-0.11	-0.15	-0.01
HFRI Fixed Income (Total)	0.41	0.37	0.53	0.06	0.04	-0.13
HFRI Macro Index	0.50	0.44	0.58	0.32	0.32	0.15
HFRI Market Timing Index	0.75	0.68	0.68	-0.04	-0.04	0.06
HFRI Merger Arbitrage Index	0.65	0.64	0.57	-0.14	-0.20	-0.08
HFRI Regulation D Index	0.53	0.55	0.44	0.04	0.05	-0.01
HFRI Relative Value Arbitrage Index	0.57	0.58	0.51	-0.12	-0.09	-0.12
HFRI Short Selling Index	-0.78	-0.77	-0.63	0.16	0.04	-0.13
HFRI Fund of Funds Composite Index	0.70	0.66	0.68	0.06	0.06	-0.05
HFRI Fund Weighted Composite Index	0.85	0.82	0.77	-0.06	-0.04	0.03

Table 6.8: Correlation coefficients between American hedge fund styles and 6 different stock and bond indices during major financial crises.

6.3. Optimal number of Hedge Funds in a portfolio

One of the things discovered in section 6.2 was that one could reduce the correlation with the stock market if one invested in portfolios of Nordic hedge funds instead of individual funds. This leads to the question of how many individual hedge funds that are needed to create an optimal risk-adjusted portfolio. This depends on the correlation between the individual Nordic hedge funds. Table 6.9 shows the cross-sectional average correlations between and within the different styles. As one can see, the correlations vary a lot from as low as 0.11 to as high as 0.65. These relatively high correlations may suggest that many of the hedge funds are exposed to the same market risks. This topic will be examined later in this thesis. But there may still be some diversification benefits of combining individual hedge funds into portfolios. To find out how many is needed, a Monte Carlo simulation will be conducted.

	Equities	Fixed Income	Multi Strategy	Managed Futures	FoHF
Equities	0.57	0.57	0.57	0.52	0.61
Fixed Income		0.64	0.58	0.54	0.57
Multi Strategy			0.55	0.11	0.27
Managed Futures				0.44	0.20
FoHF					0.65

Table 6.9: Cross-sectional average correlations between individual Nordic hedge funds.

The Monte Carlo simulation is run as follows. For each number of hedge funds in a portfolio a thousand simulations are performed. The individual hedge funds are drawn randomly from the entire sample of Nordic hedge funds with exception of FoHF's. Figure 6.1 shows the range of returns for portfolios consisting of from one through to 30 individual hedge funds. As one can see, the range of returns is getting tighter as the number of funds in the portfolio increases. From around 17-18 funds in the portfolio the range of returns is quite stable. Table 6.10 shows that the annualized Sharpe ratio increase as the number of funds in the portfolio increase, but also this becomes somewhat stable from around 15 funds and outwards. These results can therefore be interpreted in the way that 17-18 hedge funds are needed to create an optimal risk-adjusted portfolio. This is consistent with Anjilvel et. al. (2001) who found that 15-20 hedge funds are needed.

There are two more observations in figure 6.1 that is worth mentioning. Firstly, the interquartile range is very stable and close to the median. Secondly, there are indications of positive skewness in all ranges, especially for the lower numbers of funds. These observations may be interpreted in the way that the risk in hedge fund portfolios are relatively low and stable, and that most of the risk are at the upper side.

	Number of hedge funds in the portfolio					
	1	5	10	15	20	30
Annualized Sharpe	0.95	1.05	1.09	1.12	1.15	1.22

Table 6.10: Annualized Sharpe ratios for portfolios consisting of from 1 to 30 individual hedge funds.

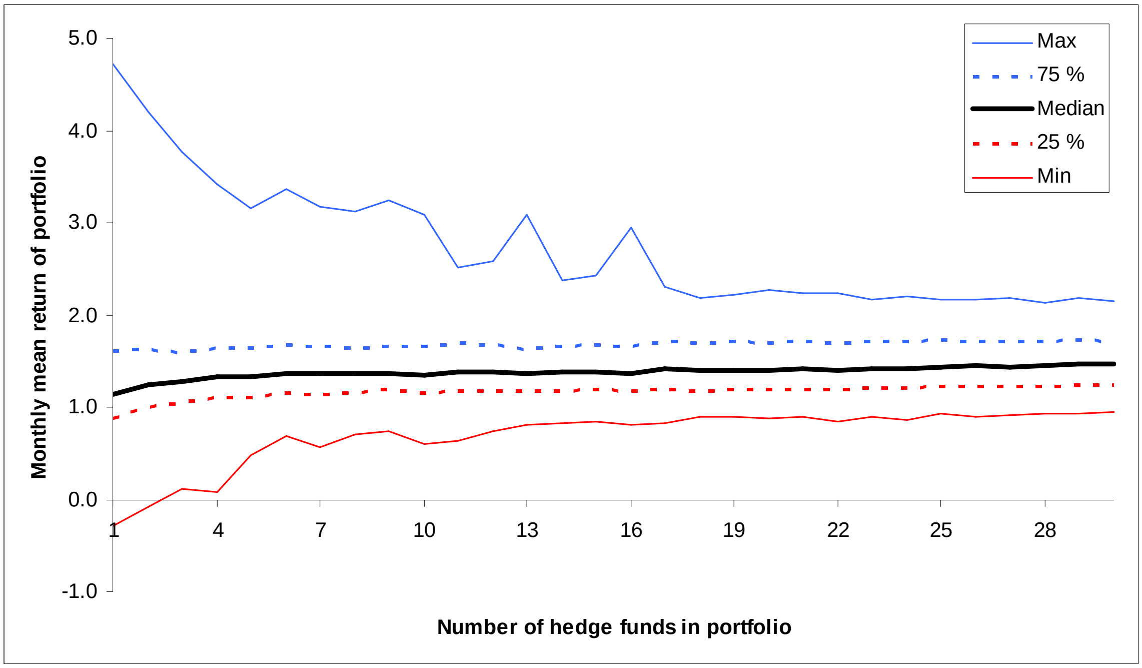

Figure 6.1: The range of returns from the Monte Carlo simulations for different number of individual Nordic hedge funds in the portfolio.

7. Performance Measurement

Chapter 5 showed that the descriptive statistics for both Nordic and American hedge funds were pretty good. Figure 7.1 illustrates this return and risk relationship. As one can see, the hedge fund indices have clearly outperformed their respective stock indices (MSCI World and MSCI Nordic). In addition the hedge fund indices have had a relatively stable development through time, indicating low risk (somewhere between stock and bond risk).

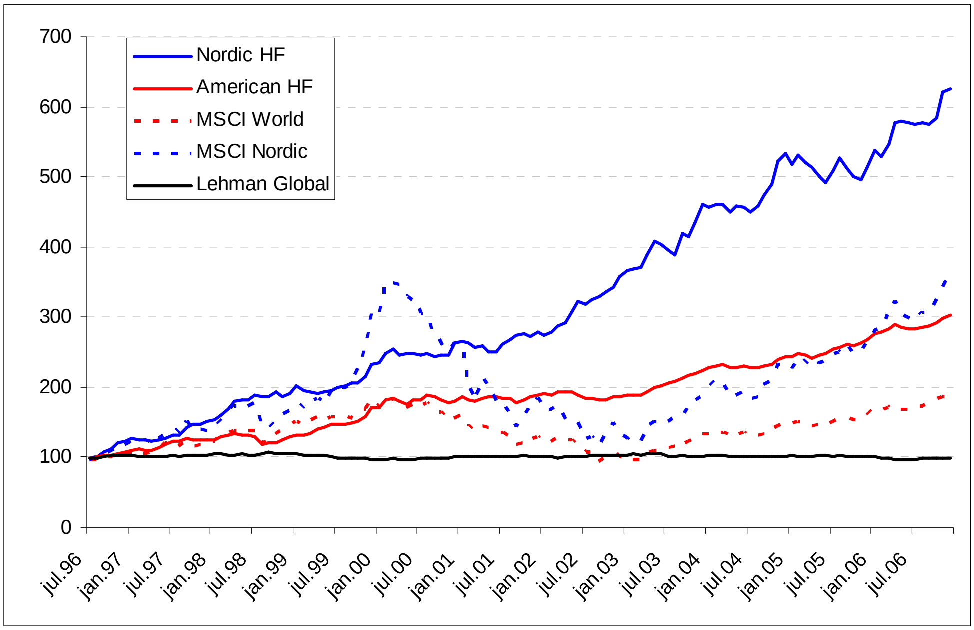

Figure 7.1: Graph showing the performance of hedge funds and the stock and bond market. (July 1996 = 100)

To further investigate this risk-return relationship, this chapter will focus on the *risk-adjusted* performance of Nordic and American hedge funds. This will be done by estimating the different absolute performance measurements presented in chapter 3.4, and comparing these to different stock, bond and commodity indices.

Previous studies like Kaplan and Knowles (2004), Bacmann and Scholz (2003), Gregoriou and Gueyie (2003) and Liang (2003) all indicate that the traditional Sharpe ratio is not a good measure for risk-adjusted performance when the return distribution exhibits negative skewness, positive excess kurtosis and/or positive autocorrelation. The need for a more robust measurement is apparent. Some of these have been presented in chapter 3.4.2. But according to Gèhin (2004) the documentation of these measurements are still a bit weak, and this should be kept in mind when they are used.

7.1. Hedge Funds vs. Stocks

In this first subchapter the performance of Nordic and American hedge funds will be commented and compared with some stock indices. Appendix 1, panel A through C, contains the estimated performance measures for Nordic and American hedge funds. In panel A the measures are the cross-sectional average of all the individual Nordic hedge funds, while in panel B and C the measures are based on Nordic and American style indices, respectively.

The annualized Sharpe ratio for the Nordic hedge funds range from around 0.62 to 1.45. The composite index has an annualized Sharpe ratio of 1.45. The range for American hedge funds is from 0 to around 1.7, and with a (Fund Weighted) composite index Sharpe ratio of 0.94 which is substantially lower than the Nordic composite index. The Nordic hedge funds seem to outperform the American ones slightly. The best Nordic style according to the Sharpe ratios is the Equities style.

The annualized Treynor ratios for Nordic and American hedge funds are very large in absolute terms. This is due to the fact that most of the hedge funds have a beta coefficient close to zero. The range for Nordic hedge funds is roughly from -10 to 1,090, while for American hedge funds the range is a lot smaller from around 0 to 110. The high Treynor ratio of the Managed Futures index is due to the fact that the beta coefficient of this index is only 0.014. The ratios for the composite Nordic and American indices are about 65 and 18, respectively. The Treynor ratio indicates that the Nordic hedge funds outperform the American ones.

The last traditional performance measurement, the Jensen's Alpha, reports annualized estimates of around 5.3 to 19.9 percent for Nordic hedge funds and around 2.5 to 8.0 percent for American funds. The MSCI World[22] index (denoted in USD) is used as a proxy for the market model in the CAPM and the estimation of alpha (and beta for the Treynor ratio). The Nordic composite index produces an annualized alpha of 13.2 percent, while the American counterpart "only" produces 5.9 percent. Yet again the Nordic funds outperform the American funds.

The autocorrelation-adjusted Sharpe ratios for the cross-sectional average individual Nordic hedge funds are all higher than their regular Sharpe ratios (except for Fixed Income). This should, according to Lo (2002), indicate that there is relatively little significant *positive* autocorrelation for the average *individual* hedge fund (positive autocorrelation can lead to overestimation of the true Sharpe, i.e. the regular Sharpe ratio would be higher than the autocorrelation-adjusted Sharpe if positive autocorrelation exists). That is consistent with the relatively low fraction of individual autocorrelations documented in panel A of table 5.1. At the *index* level of Nordic hedge funds, only the Equities index has a lower autocorrelation-adjusted Sharpe ratio than its regular Sharpe ratio. This indicates that there might exist significant positive autocorrelation in this index. Again this is backed up by the autocorrelation estimate of table 5.1 (panel B). For the American hedge fund indices most of them exhibit lower autocorrelation-adjusted Sharpe ratios, which indicate that relatively many indices have significant positive autocorrelation. This is also consistent with the estimates of table 5.3 where 11 out of 16 indices exhibits significant autocorrelation.

The modified Sharpe ratios of both Nordic and American hedge funds are all lower than the regular Sharpe ratios. This is not surprisingly since the estimates in table 5.1 and 5.3 indicate that most of the hedge funds exhibit non-neglectable skewness and excess kurtosis. According to Gregoriou and Gueyie (2003) this leads to overestimation of the true Sharpe ratio.

[22] The reason why this index is used as a proxy instead of i.e. MSCI Nordic or MSCI US, is that this index covers both the Nordic and American markets. Since Nordic and American hedge funds will be compared, the use of the same index is preferable.

The range of the annualized autocorrelation-adjusted Sharpe ratios for Nordic and American hedge funds is 0.5-1.5 and 0-1.4, respectively. For the modified Sharpe ratio the ranges are 0.3-0.7 and 0-0.7, respectively. The estimates for the composite indices are also better for the Nordic hedge funds for both transformations of the Sharpe ratio.

The three last performance measurements, the Sortino ratio, the Omega and the Kappa, are all somewhat related. The Sortino ratio have more focus on downside risk (or negative skewness), the Omega can be interpreted as a ratio between upside potential and downside risk, while the Kappa (with n=3) is more a technical measure with no easy interpretation. Common for them all is that they are very much alike for Nordic and American hedge funds.

In panel D of appendix 1, the same performance measurements for 8 different stock indices are presented (all denoted in USD). Four regional indices (World, US, Europe and Nordic), and the same four expressed for small cap stocks only.

The first point worth noticing in panel D is that the annualized Sharpe ratios for the stock indices are significantly lower that for the hedge funds (both Nordic and American). The highest Sharpe ratio for the stock indices is the MSCI Nordic Small Cap with 0.61. There are only three estimates of the Sharpe ratios for hedge funds that are lower than that. The Treynor ratios for the stock indices range from 2.4-11.9, which also is substantially lower than for hedge funds. The estimates for Jensen's Alpha for the stock indices are somewhat lower than those of the hedge funds with a range of 0-8.9.

By only looking at the traditional performance measurements, the Nordic and American hedge funds seem to outperform general stock indices. But the interesting question is whether this is due to the fact that hedge fund returns exhibit positive autocorrelation and non-neglectable skewness and excess kurtosis. To clarify this it is useful to look at the more modern measurements (from chapter 3.4.2) which adjust for this. But unfortunately for the stock indices this does not help. They are still outperformed by hedge funds. The highest estimates of the modern measures for the stock indices are only strictly higher than a few hedge fund estimates – mainly for the HFRI Short Selling and HFRI Emerging Markets indices.

In appendix 2 the Spearman's rank correlation coefficients between all the performance measures are presented. These coefficients show the correlation between the rankings of the indices/averages within a panel based on the different performance measures. A coefficient of 1.0 indicates that the two performance measurements in question rank the indices/averages in the same way.

	Mean	Std.error	t-statistic	P-value
Panel A: Average individual hedge fund (Nordic)	0.53	0.09	-4.90	0.0000
Panel B: Hedge fund indices (Nordic)	0.59	0.07	-5.13	0.0000
Panel C: Hedge fund indices (American)	0.55	0.06	-6.70	0.0000
Panel D: Stock indices	0.95	0.01		

Table 7.1: Results of a two-sample t-test for the difference between the average Spearman's rank correlation coefficients for hedge funds and stocks in appendix 2.

Table 7.1 shows the average correlation coefficients of panel A-D of appendix 2. The average coefficients for hedge funds range between 0.53 and 0.59 and for stocks the average is 0.95. All the averages are statistically different from 1.0 which indicates that there exists some difference in the rankings between the different performance measurements. The relatively low averages for hedge funds indicate that the rankings based on the different performance measurements are more inconsistent. For stocks on the other hand, the rankings are more consistent (indicated by a relatively high average correlation coefficient). This can be interpreted in the way that the choice of performance measure is more important for hedge funds since they produce relatively different rankings. This is also consistent with the fact that hedge funds exhibit more autocorrelation, skewness and excess kurtosis than stocks (chapter 5) and has therefore more use for more alternative and modern measurements. The t-statistics and the p-values for the hedge fund averages indicate that they are all statistically different from the average for stocks.

7.2. Hedge Funds vs. Bonds

Panel E of appendix 1 show the performance measurements for four different bond indices – one global, two US and one Nordic. The Nordic index is an equal-weighted average of the indices Handelsbanken Norway, Sweden, Finland and Denmark (all denoted in USD).

The first point to notice is that all the Sharpe ratios (both regular and adjusted/modified) and Jensen's Alpha are negative. This is due to the fact that the four indices all have lower average periodic return than the risk free rate. This is somewhat unusual, but is probably a result of the selection of sample time period.

The autocorrelation-adjusted Sharpe ratios of bonds are all close to the regular Sharpe, which indicates that autocorrelation is not a problem for bond returns. This is more or less confirmed by table 5.2 where only the Handelsbanken Nordic index exhibit significant autocorrelation. When it comes to the modified Sharpe ratios they are all higher than their regular counterpart, which should suggest that bond returns are not normally distributed. Again this is confirmed by table 5.2.

All the Omega measures are close to 1.0 which can be interpreted in the way that the upside potential and downside risk in the bond indices are pretty much the same.

When the performance measures for bonds are compared to those of hedge funds, a pretty clear picture arises. All the measures are by far worse for bonds than for hedge funds. The only small exception may be the Treynor ratios for bonds which sometimes are slightly better than those of American hedge funds.

	Mean	Std.error	t-statistic	P-value
Panel A: Average individual hedge fund (Nordic)	0.53	0.09	0.35	0.7286
Panel B: Hedge fund indices (Nordic)	0.59	0.07	0.86	0.3947
Panel C: Hedge fund indices (American)	0.55	0.06	0.57	0.5755
Panel E: Bond indicies	0.48	0.11		

Table 7.2: Results of a two-sample t-test for the difference between the average Spearman's rank correlation coefficients for hedge funds and bonds in appendix 2.

Table 7.2 show the same statistics as table 7.1, but now the average hedge fund correlations are compared with the average rank correlations for the bond market. The average Spearman's rank correlation coefficient for bonds is 0.48 and is statistically different from both stocks and the value 1.0. This relatively low average indicates that the choice of performance measure may make a difference for the ranking of the bond indices. The t-statistics and p-values in table 7.2 show that none of the three average rank correlations for hedge funds are statistically different from the bond average.

7.3. Hedge Funds vs. Commodities

Panel F of appendix 1 show the performance of 7 different commodity indices. There are one overall commodity index and 6 specific indices representing crude oil, gold, energy, aluminum, copper and natural gas.

The annualized Sharpe ratios range from 0.0 to 0.4 with crude oil and energy being the best performers. But every index performs worse than all hedge funds except for the American HFRI Short Selling index. The Treynor ratios and the Jensen's Alphas are also worse for commodities, but only slightly.

The autocorrelation-adjusted Sharpe ratios for the commodity indices are very similar to those of the regular Sharpe. This indicates little significant autocorrelation in the returns. As for the regular Sharpe ratios these adjusted ratios are all lower for commodities than for hedge funds with exception of a few indices. When it comes to the modified Sharpe ratio, these estimates are all lower than their regular counterparts. Some skewness and excess kurtosis can therefore be expected in the return distribution for commodities. Compared to hedge funds these ratios are mostly lower for commodities. The three last measures are also all mostly lower for commodities than for hedge funds.

	Mean	Std.error	t-statistic	P-value
Panel A: Average individual hedge fund (Nordic)	0.53	0.09	-1.31	0.2019
Panel B: Hedge fund indices (Nordic)	0.59	0.07	-0.81	0.4262
Panel C: Hedge fund indices (American)	0.55	0.06	-1.33	0.1946
Panel F: Commodities	0.67	0.07		

Table 7.3: Results of a two-sample t-test for the difference between the average Spearman's rank correlation coefficients for hedge funds and commodities in appendix 2.

Table 7.3 shows the same statistics as table 7.1 and 7.2, but now the hedge funds are compared with commodities. The average Spearman's rank correlation coefficient between different performance measurements for commodities is 0.67, which lies in between the averages for stocks and bonds. The estimate is significantly different than 1.0 which indicates that the different measures do in fact rank differently. The relatively low average coefficient for commodities means that the choice of performance measure is important. Again, none of the average Spearman's rank correlation coefficients for hedge funds is statistically different from the average for commodities.

8. Can Hedge Fund Returns be Explained by Asset Pricing Models ?

The focus of this chapter will be to test if some asset pricing models can explain the return of Nordic hedge funds. The asset pricing models that will be used is the CAPM, the adjusted CAPM, the Four Factor Model, an Explicit macro-factor model and an Implicit factor model.

8.1. The CAPM

First out is the traditional CAPM. It has long been thought that this model describes the return of traditional assets relatively well. But in the recent decade or so, much research has been published that questions the model. It may therefore be interesting to see if this also applies to Nordic hedge funds.

To test the CAPM, the Market Model in equation (3.7) is used. The parameters are estimated via an OLS regression, and the error terms are assumed to be i.i.d. The most important issue when testing the CAPM, is the choice of proxy for the market portfolio. In theory it should be an asset-weighted portfolio consisting of every asset in the market. Such a portfolio is very difficult to obtain (if not impossible) and therefore a broad index is used as a proxy. But there exist many “broad” indices, and it also depends on the investment universe of the funds in question. In this thesis the MSCI Nordic (denoted in USD) will be used as a proxy. The reason for this is that the funds in question are Nordic even though many of them invest in markets outside the Nordic region. But the choice of either MSCI World or MSCI Europe would not have made much difference. Appendix 3 shows the distribution of alphas under the three proxies. Although they produce somewhat different distributions and means, they will all have significant alphas on average.

Table 8.1 shows the different model statistics as estimated by the CAPM. The alphas should be zero if CAPM is a good model for describing the return of Nordic hedge funds. For the equally-weighted composite index (of hedge funds), the monthly alpha is just over 1%. The p-value shows that this alpha is (highly) statistically different from zero. The cross-sectional average alpha of all individual hedge funds is 0.39%, and also this is statistically different from zero. Table 8.1 also shows that 27.1% of the individual hedge funds have significantly *positive* alpha, while only 0.9% have a significant *negative* alpha. All these statistics indicate that the CAPM is a poor model in describing the return of the *average* Nordic hedge fund. To test the rejection of CAPM, one would have to test if *all* the alphas were zero at the *same* time. One way to do this is to calculate the GRS-statistic of Gibbons, Ross and Shanken (1989), but this requires all the funds to have equally long return history. That is not the case in this study of Nordic hedge funds.

	Composite Index	Average individual fund
Alpha (monthly), %	1.02	0.39
Std. Error Alpha (monthly), %	(0.22)	(0.06)
P-value (for Alpha not 0)	0.0000	0.0000
Beta	0.17	
Std. Error Beta	(0.03)	
R-squared	0.1965	
Percent of funds with Alpha significant > 0	27.1 %	
Percent of funds with Alpha significant < 0	0.9 %	

Table 8.1: Model statistics as measured by the CAPM (standard errors are reported in parentheses).

Figure 8.1 shows the distribution of monthly alphas under the CAPM. There is a wide spread of alpha estimates, and this strengthens the belief that the CAPM describes the returns poorly for Nordic hedge funds. These results in table 8.1 and figure 8.1 are in line with those of Amenc and Martellini (2003). They use the same approach on 581 individual American hedge funds.

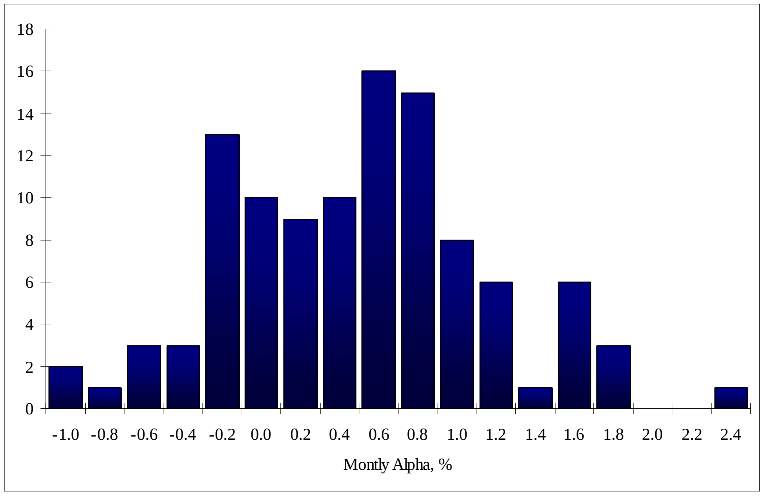

Figure 8.1: Distribution of monthly alphas as measured by CAPM.

Appendix 6 shows the results from a test of CAPM where the proxy for the market portfolio is estimated with a so-called principal component analysis, PCA[23]. This method extracts an orthogonal market portfolio from a subset of 7 different broad MSCI stock indices (World, US, Europe, Norway, Sweden, Denmark and Finland) in excess of the risk-free rate. This more or less eliminates the problem of which proxy to use for the market portfolio. The result of the analysis is very similar to those in table and figure 8.1. The only small differences are that the monthly alphas in appendix 6 are a bit higher (1.14% and 0.51%).

8.2. The adjusted CAPM

Asness, Krail and Liew (2001) argue that the test of CAPM conducted under chapter 8.1 can be misleading due to stale or managed prices. Many hedge funds hold illiquid exchange-traded securities or difficult to trade over-the-counter securities which are difficult to mark (can not use mark-to-market), and these securities lead to non-synchronous movements in the returns. Such non-synchronous return data can lead to understated estimates of actual market exposure (Asness, Krail and Liew, 2001).

[23] PCA will be described later in this chapter.

One simple solution to this problem is to use longer horizon returns, i.e. quarterly (Asness, Krail and Liew, 2001). A more "complex" solution is to include lagged values of the explanatory variable (the excess return on the market portfolio). This concept was first introduced by Dimson (1979) and Scholes and Williams (1977), and is estimated with equation (8.1).

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=0}^{K} \beta_{ik}\left(R_{M,t-k} - R_{f,t-k}\right) + \varepsilon_{i,t} \qquad (8.1)$$

This approach will be used in this thesis, with K=3 (in accordance with Asness, Krail and Liew (2001) and Amenc and Martellini (2003)). Again the question arises on which proxy to use as a market portfolio. In order to be consistent with the previous subchapter, the MSCI Nordic will be used. Appendix 4 show that the distribution of alphas under different proxies for the market portfolio. Using MSCI Nordic and MSCI World yields pretty much the same results, while MSCI Europe is quite different with a negative cross-sectional average alpha (due to some extreme negative outliers).

Table 8.2 shows the model statistics as measured by the adjusted CAPM. The results are very much the same as in table 8.1 for the composite index, while the cross-sectional average individual alpha is more than halved. It has also become insignificant. The percentage of funds that have a significant positive alpha have also decreased to 22.4%, while the amount of funds with negative alpha has increased to 2.8%.

	Composite Index	Average individual fund
Alpha (monthly), %	0.98	0.14
Std. Error Alpha (monthly), %	(0.22)	(0.08)
P-value (for Alpha not 0)	0.0000	0.1061
Beta(k=0)	0.17	
Std. Error Beta(k=0)	(0.03)	
Beta(k=1)	0.03	
Std. Error Beta(k=1)	(0.03)	
Beta(k=2)	0.02	
Std. Error Beta(k=2)	(0.03)	
Beta(k=3)	0.01	
Std. Error Beta(k=3)	(0.03)	
R-squared	0.2072	
Percent of funds with Alpha significant > 0	22.4 %	
Percent of funds with Alpha significant < 0	2.8 %	

Table 8.2: Model statistics as measured by the adjusted CAPM where K=3 (standard errors are reported in parentheses).

The distribution of alphas under the adjusted CAPM is shown in figure 8.2. There are a few more alphas that are negative in this figure than in figure 8.1, but the majority is still positive. Both table and figure 8.2 indicate that the use of the adjusted CAPM describes the returns a bit better than the regular CAPM, especially for individual funds. These results are somewhat in line with those of Asness, Krail and Liew (2001) and Amenc and Martellini (2003). They find that both indices and individual hedge funds does not produce significant alpha when this correction for stale or managed prices is made.

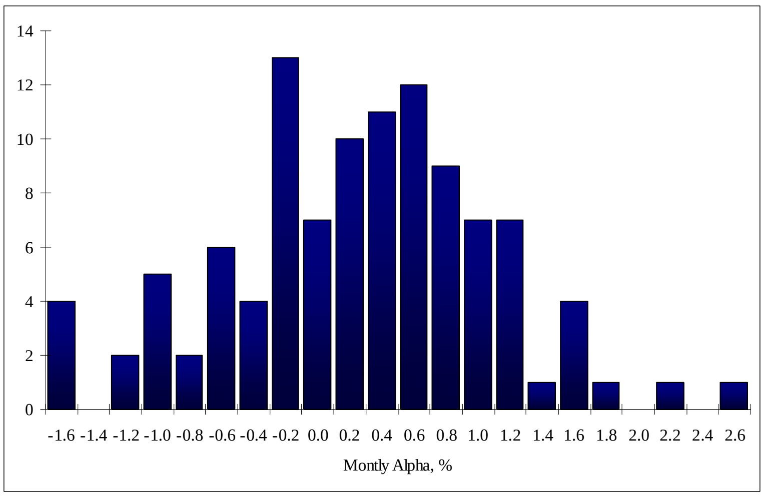

Figure 8.2: Distribution of monthly alphas as measured by the adjusted CAPM.

8.3. The Four Factor Model

In 1993 Fama and French published an article that was the birth of their Three factor model. After that, the model has been a popular alternative to the traditional CAPM. Many researchers have tested the model, with different results. In general the model does better than the CAPM. Some argue that it is much better, while other is of the opinion that the gain of including 2 more factors is too little compared to the extra effort (Bartholdy and Peare, 2005).

That same year, and later in 2001, Jegadeesh and Titman published two articles that document the momentum effect. They argued that there exists some momentum effect on shorter horizons (3-12 months).

In recent years these two models have been linked together into the so-called Four factor model. This model will now be used to see if it can describe the return of Nordic hedge funds. As for the two last subchapters, the proxy for the market portfolio will be the MSCI Nordic index. Appendix 5 shows that the choice of proxy is not that sensitive for the Four factor model as for the previous models. All proxies yield more or less the same cross-sectional averages, perhaps with the exception of MSCI World. But all three proxies conclude in the same way. The factors SMB, HML and UMD are based on American data, and should strictly speaking only be used for American hedge funds. But in this thesis they are also used on Nordic hedge funds. The reason for this is that if these factors should have been computed from scratch, it would have demanded a lot of Nordic accounting data which is relatively difficult and time-consuming to collect. This may have some impact on the estimated alphas, but is difficult to say without actually performing the analysis on Nordic accounting data. On the other hand, the consequences may not be that severe since many of the funds invest globally.

	Composite Index	Average individual fund
Alpha (monthly), %	0.88	0.04
Std. Error Alpha (monthly), %	(0.22)	(0.09)
P-value (for Alpha not 0)	0.0001	0.6608
Beta(Market portfolio)	0.20	
Std. Error Beta(Market Portfolio)	(0.04)	
Beta(SMB)	0.02	
Std. Error Beta(SMB)	(0.06)	
Beta(HML)	0.07	
Std. Error Beta(HML)	(0.07)	
Beta(UMD)	0.10	
Std. Error Beta(UMD)	(0.04)	
R-squared	0.2460	
Percent of funds with Alpha significant > 0	18.7 %	
Percent of funds with Alpha significant < 0	2.8 %	

Table 8.3: Model statistics as measured by the Four factor model (standard errors are reported in parentheses).

The estimated monthly alphas of table 8.3 are slightly lower than for the adjusted CAPM, but the conclusion is the same. Only the composite index has a significant alpha. 18.7% of the individual funds have significant positive alpha, while only 2.8% have significant negative alpha. These numbers are roughly the same as for the previous model.

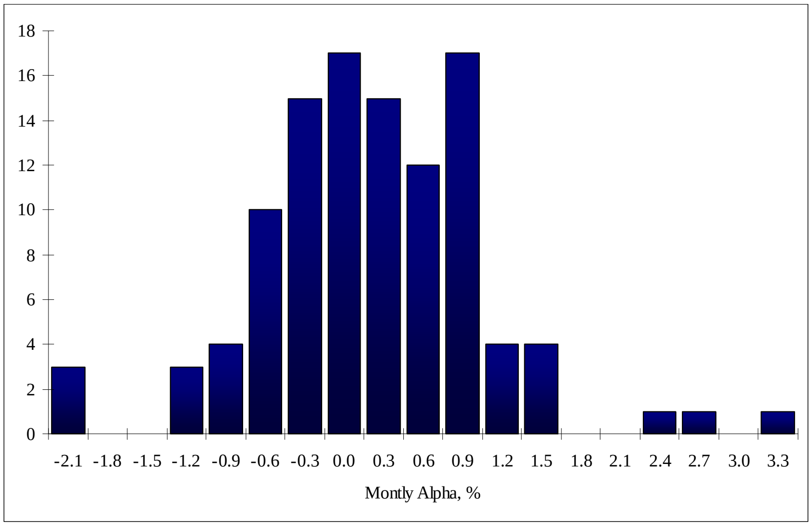

Figure 8.3: Distribution of monthly alphas as measured by the Four factor model.

Figure 8.3 shows the distribution of alphas under the Four factor model. Now the alphas are more evenly distributed above and below zero. The conclusion for this model is the same as for the adjusted CAPM. It does not describe the returns of the composite index, but it works relatively fine for the average individual fund.

8.4. Explicit macro-factor model

According to Gèhin (2004) the three most important multifactor models for hedge funds are; (1) the Explicit micro-factor model, (2) the Explicit macro-factor model, and (3) the Implicit factor model. The first model tries to explain hedge fund returns with fund-specific factors. In the past this has been proven to be difficult (De Souza and Gockan, 2003). The sample used in this thesis is somewhat limited when it comes to the completeness of the panel dataset of fund-specific factors. This has lead to the exclusion of this model in this chapter, but instead some of the fund-specific factors will be covered individually later in this thesis (chapter 9.3). The second model will be used in this subchapter, while the third model will be covered in the next subchapter.

The explicit macro-factor model tries to explain Nordic hedge fund returns through the inclusion of different observable market risk factors. The choice of factors may lead to non-negligible mis-specification risk. In this thesis the factors are selected using the same logic as in Ammann and Moerth (2005) and Agarwal and Naik (2000a), and they are:

- MSCI World
- MSCI Nordic
- MSCI Emerging Market
- MSCI World Small Cap
- MSCI Nordic Small Cap
- Lehman US Government
- Lehman US High Yield
- Handelsbanken Nordic
- Bloomberg European Commodity Index
- IPE Brent Crude Oil
- Englehard Gold Bullion Spot
- CBOE SPX Volatility Index

All the asset class factors and hedge fund returns are in excess of the risk-free rate, with exception of the CBOE SPX Volatility Index since this is not an asset class in the traditional sense (Ammann and Moerth, 2005).

The analysis for the explicit macro-factor model is conducted in two different ways. First a regular multiple OLS regression with all the independent factors is run. This is done for all individual Nordic hedge funds and for the composite index. Due to collinearity between some of the independent variables, the 16 individual hedge funds with the fewest observations are excluded from the regressions. This is done automatically in STATA. The results from these regressions are presented in table 8.4. The second analysis uses a stepwise regression[24] to estimate the alphas for all individual funds (still excluding 16 funds due to collinearity) and the composite index. This second approach is the most used approach in previous studies. The reason is that it tries to account for the collinearity between the independent variables in the analysis which still may be a problem even though 16 funds have been removed for this reason. The results of these stepwise regressions are presented in table 8.5. The average number of factors in the stepwise regressions for individual funds is 2.1, while the regression for the composite index includes 4 factors (MSCI Nordic, MSCI Nordic Small Cap, Handelsbanken Nordic and CBOE SPX Volatility Index).

The results from the explicit macro-factor model in table 8.4 and 8.5 are quite similar to the previous two models. The conclusions for both the composite index and the cross-sectional average are more or less identical, but perhaps with slightly lower alpha estimates. The fraction of funds with significantly positive alpha is somewhat lower in the multiple regressions, while the proportion of funds with negative alphas has increased a bit (especially for the stepwise regression).

The estimates in table 8.5 are slightly better than the same estimates in table 8.4, indicating that collinearity may be non-neglectable. The average monthly alpha for the individual funds in table 8.5 is -0.01% which is somewhat better than in table 8.4 (-0.05%). The percentage of funds with significant positive alphas is also higher in table 8.5 (20.9% vs. 14.3% in table 8.4).

	Composite Index	Average individual fund
Alpha (monthly), %	0.81	-0.05
Std. Error Alpha (monthly), %	(0.19)	(0.09)
P-value (for Alpha not 0)	0.0000	0.6351
R-squared	0.6125	
Percent of funds with Alpha significant > 0	14.3 %	
Percent of funds with Alpha significant < 0	5.5 %	

Table 8.4: Model statistics as measured by a multiple regression on the explicit macro-factor model (standard errors are reported in parentheses). Beta coefficients are left out (they will be reported in chapter 9.2 and appendix 8).

[24] A stepwise regression is a technique that involves adding independent variables according to their significance. One start with an empty model and adds the single most significant variable first. Then the second most significant variable is added, and so on. All the variables that are added have to be significant at a 5% level.

	Composite Index	Average individual fund
Alpha (monthly), %	0.88	-0.01
Std. Error Alpha (monthly), %	(0.18)	(0.08)
P-value (for Alpha not 0)	0.0000	0.8878
R-squared	0.5849	
Percent of funds with Alpha significant > 0	20.9 %	
Percent of funds with Alpha significant < 0	13.2 %	

Table 8.5: Model statistics as measured by a stepwise regression on the explicit macro-factor model (standard errors are reported in parentheses). Beta coefficients are left out (they will be reported in chapter 9.2 and appendix 8).

Figure 8.4 shows the distribution of monthly alphas for the two types of regression methods used on the explicit macro-factor model. The multiple regressions produce a slightly wider spread of alphas due to some extreme negative estimates, while the stepwise regressions have a more centralized distribution.

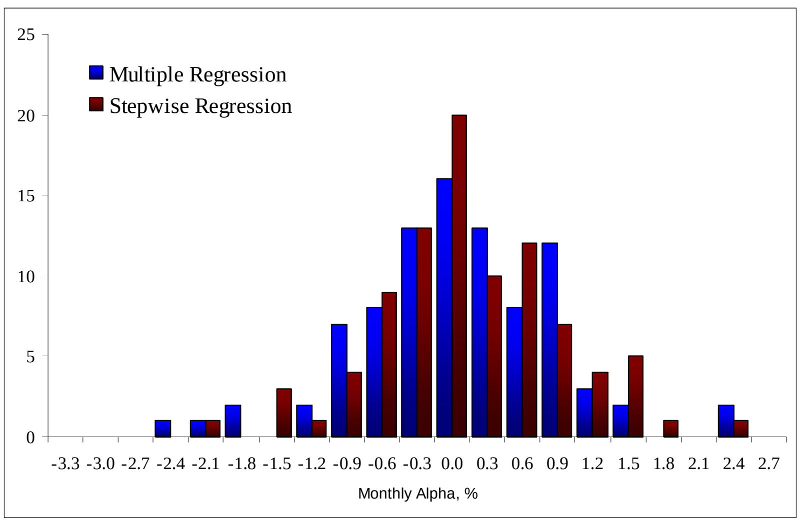

Figure 8.4: Distribution of monthly alphas as measured by the Explicit macro-factor model.

8.5. Implicit factor model

This last model is a purely statistical approach which obtains the implicit independent factors through a Principal Component Analysis (PCA). The purpose of this approach is to try to explain the hedge fund return series trough a small group of non-observable implicit variables which is defined as a linear combination of the primary variables. The advantage of this type of approach is that it eliminates the variable selection problem.

This avoids under- or over-specifying the model. The disadvantage is that the economic interpretation of the model and its variables is relatively poor (except for the first factor which often has a large correlation to the market index).

Usually the analysis is conducted on *balanced* panel dataset of returns, but in this thesis the panel is *unbalanced*. This leads to a small problem when it comes to the estimation of the principal components (PC's). To overcome this problem, four separate PCA's are conducted. The first analysis estimates the PC's from all the hedge funds that are registered as of January 2002. This creates 3 PC's[25]. Then all of these PC's are used as independent variables in an OLS regression with the individual hedge funds and the composite index as dependent variables. Estimates of alphas are then obtained. The second analysis does the same for all the funds that are registered as of January 2003 (4 PC's are formed). The third analysis for funds registered as of January 2004 (4 PC's are formed), and the last analysis for funds that are registered as of January 2005 (7 PC's are formed). All the analyses are run on *excess* returns (over the risk-free rate).

The estimated alphas from these four PCA's are presented in appendix 7. All of the analyses produce more or less the same results with significantly monthly alphas around 0.46-1.10% (both for the composite indices and the cross-sectional individual averages). For the composite index the monthly alphas are roughly in the same ballpark as the other models in this chapter, while the cross-sectional average alphas for individual funds are higher for this model than the previous models.

The percentages of funds with significant positive alphas range from around 43-79%, which is substantially higher that for the other models in this chapter. For funds with significant negative alphas, the percentage range from 0-2%. This is in the same range as for the first models, but somewhat lower than for the Explicit macro-factor model (especially for the stepwise regression).

[25] Only significant PC's are used in the further analysis. Significant means that they have an estimated eigenvalue of at least 1.

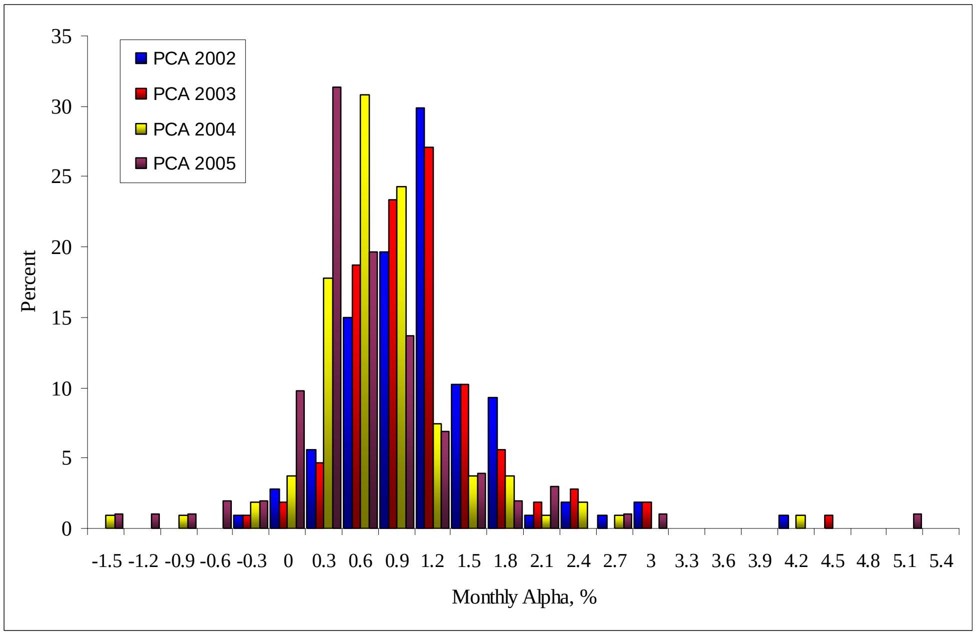

Figure 8.5: Distribution of monthly alphas as measured by the four PCA's for the implicit factor model.

The distribution of alphas for the four analyses of the implicit factor model is presented it figure 8.5. The distributions are pretty much the same with a large proportion of the alphas being positive. These results all indicate that the implicit factor model do not describe the Nordic hedge fund returns well.

9. Sources of Hedge Fund Return and Risk

So far this thesis has painted a pretty good picture of Nordic hedge funds' return and risk. The descriptive statistics were very good and did not suffer from non-favorable higher order moments as much as previous studies. The correlations were also very good even in bear markets and during financial crises. Chapter 7 revealed that the risk-adjusted performance were extraordinary compared to the traditional asset classes. So what is it about Nordic hedge funds that make them appear so good? The answer to that is the main purpose of this chapter. Here the sources of return and risk will be explored, both macro factors and micro factors.

9.1. Previous studies

Many people suspect that the good performance of hedge funds can be attributed to loading of general market risk. Agarwal and Naik (2000b) show that different types of macro factors influence different types of hedge funds. Kat and Lu (2002) find that only 10-20% of the variation in the average hedge fund's return can be explained by the general stock and bond market. In contrast, this proportion is usually 80% or more for regular mutual funds. Amenc and Martellini (2003) use 581 individual hedge funds to examine the CAPM-beta. They find a significant (annual) beta of 0.373 for the average hedge fund.

Much more research has been conducted on fund specific, or micro, factors like age of fund, size of fund, managers experience and education, fees, redemption period, minimum investment amount, and so on. When it comes to size, the results are somewhat contradicting. Gregorious and Rouah (2002) find no significant relationship between size and performance, while Brorsen and Harri (2004) find a significant negative relationship. Their hypothesis is that the inefficiencies that the managers are supposed to exploit in the market are limited. For them to be able to produce a respectable return from these inefficiencies they need to close the funds to new investors and this prevents the funds from growing. Koh, Koh and Teo (2003), Amenc and Martellini (2003), De Souza and Gokcan (2003), Chen and Ibbotson (2005) and Liang (1999) all find a positive relationship between size and performance. Getmansky (2005) and Ammann and Moerth (2005) also find a positive relationship, but in addition the relationship is concave. Their hypothesis is that funds with bad performance have problem attracting new investors or that larger funds have lower average fees.

Kat (2003a), Howell (2001) and Amenc and Martellini (2003) all find that young hedge funds outperform older funds. Kat (2003a) point out that this may be due to the fact that the young funds that reports to the databases are those who have survived the first difficult years where they perhaps take on a lot of risk. Many young funds die and will therefore not rapport to the database. But Howell (2001) adjusts for this survivorship bias, and still finds that young funds outperform older funds. De Souza and Gokcan (2003) on the other hand find the relationship between age and performance to be positive. Older funds outperform younger ones.

Boyson (2003) have studied the relationship between manager’s experience and performance. The author finds that one extra year of experience reduces the mean annual return with 0.8%, and that this could be due to the notion that increased experience leads to a decrease in risk aversion which again leads to a decrease in returns.

De Souza and Gokcan (2003) and Amenc and Martellini (2003) find the relationship between performance fee and returns to be positively correlated. Koh, Koh and Teo (2003) on the other hand, find this relationship to be negative. Funds with high performance fees tend to have lower mean post-fee returns. Kazemi, Martin and Schneeweis (2001) find no significant relationship between these variables.

Koh, Koh and Teo (2003) find that Asian hedge fund returns are positively affected by the redemption period, and that the minimum investment amount does not affect the returns. Kazemi, Martin and Schneeweis (2001) also find a positive relationship between the redemption period and the mean return of hedge funds. De Souza and Gokcan (2003) show that the investment of the managers own money in the fund also have a positive influence of the funds return. The same goes for the lockup and redemption period.

9.2. Standard market exposure

Agarwal and Naik (2000a) used an explicit macro-factor model to examine the influence of different broad market indices on American hedge fund indices. Again a stepwise regression was used to try to control for the collinearity between the independent variables (as done in chapter 8.4). Table 9.1 shows a similar regression on the five Nordic hedge fund indices. This stepwise regression uses the same 12 independent variables as under chapter 8.4, but only the ones with significant loadings are shown.

The most important macro factor is the Handelsbanken Nordic index. All the hedge fund indices have positive loadings against this factor. This index is an equally-weighted index of the four Nordic country's bond rates. The Fixed Income and the Managed Futures have a high positive loading against this factor (coefficient > 1). The funds in these indices operate in the fixed income market, and it is not surprisingly that they have high loadings against bond rates. The remaining four hedge funds indices have varying degrees of loadings against this factor, with FoHF's having the lowest.

Four of the hedge fund indices have significant positive loadings against the MSCI Nordic index, with Equities having the highest loading. This is not surprisingly since many of the funds in this category operate in the Nordic equity market. An interesting observation is that the MSCI World index did not produce any significant loadings. This may indicate that the choice of using MSCI Nordic instead of MSCI World as a proxy for the market portfolio in the previous chapters was a correct decision.

In addition to the two previously discussed macro factors, four other factors have some influence on the Nordic hedge fund indices. FoHF's have a positive loading against the MSCI World Small Cap index which may indicate that they invest more in global small cap funds instead of Nordic equity funds. Three indices (Equities, FoHF's and the composite) have positive loadings against the Volatility Index. Volatility is important for every hedge fund trader, especially for *equity* traders, and the positive loading against this factor seems reasonable for this index. Managed Futures has a positive loading against the Gold index. Again this seems reasonable since these types of funds trade in the futures market where gold futures are relatively common. Finally, the composite index has a positive loading against the MSCI Nordic Small Cap index indicating that the overall Nordic hedge fund market also has loadings against Nordic *small* cap stocks and not just Nordic stocks in general.

	MSCI Nordic	MSCI Nordic Small Cap	MSCI World Small Cap	Handelsbanken Nordic	Englehard Gold Bullion Spot	CBOE SPX Volatility Index
Equities	0.272			0.437		0.074
Fixed Income	0.101			1.029		
Multi Strategy	0.138			0.780		
Managed Futures				1.284	0.214	
FoHF			0.423	0.233		0.042
Composite	0.123	0.119		0.538		0.041

Table 9.1: Loadings from a stepwise regression with 12 independent variables. Only the ones that are significant are shown in the table.

For the sake of completeness, the results of the multiple regressions with all the 12 macro factors as independent variables are reported in appendix 8. This type of regression may be more exposed to collinearity, but it still produces results that are very much in line with the stepwise regression. The most important factors in the multiple regressions are the three Nordic indices MSCI Nordic, MSCI Nordic Small Cap and the Handelsbanken Nordic.

9.2.1. Stock market exposure

Since the MSCI Nordic index seems to have a significant influence on most of the hedge fund indices, it may be interesting to take a closer look at the Nordic hedge fund indices exposure to the country specific stock markets.

Table 9.2 shows the results from a stepwise regression for the Nordic hedge fund indices where the independent variables are the four country's respective MSCI index. The Swedish MSCI index is the index which has the only influence on the two largest hedge fund indices (accounts for around 74%[26] of the total Nordic hedge fund market). This does not come as a surprise since around half of all Nordic hedge funds operate from Sweden. What may seem a bit more surprisingly is the fact that MSCI Sweden does *not* affect the composite index. This index is only affected by MSCI Norway and MSCI Denmark. Finally, the Multi Strategy index is influenced by the MSCI Norway index. This is somewhat logic since one third of the funds in this category operate from Norway.

	MSCI Norway	MSCI Sweden	MSCI Denmark	MSCI Finland
Equities		0.194		
Fixed Income				
Multi Strategy	0.176			
Managed Futures				
FoHF		0.188		
Composite	0.119		0.118	

Table 9.2: Loadings from a stepwise regression for the indices where the county specific MSCI indices are the independent variables.

It may also be very interesting to see how the market exposure for *individual* Nordic hedge funds is. The middle column of table 9.3 shows the cross-sectional average individual beta (against the MSCI Nordic index denoted in USD) for different styles. It shows that all the averages are statistically different from zero and ranging from around 0.165 to 0.408. The highest cross-sectional average of 0.408 appears in the Managed Futures category. This is somewhat surprisingly since one would expect that these funds are more influenced by the fixed income market and not the equity market. Fixed Income

[26] See figure 2.4.

on the other hand, has the lowest average beta and this is more in line with what one could expect. The rest of the average beta coefficients are around 0.3. These significant betas are consistent with the average individual correlations in panel B of table 6.1 where the range of correlations is 0.25-0.45. These results show that some of the good performance for hedge funds can be attributed to the fact that they hold general stock market risk, and this is not in line with the notion that hedge funds are (fully) market neutral.

The last column of table 9.3 shows the percentage of individual hedge funds that have a beta estimate *not* statistically different from zero. For Fixed Income and Managed Futures the percentages are quite high with 70 and 50 percent, respectively. The percentages for the rest of the styles are considerably lower and range from around 30-40%, and about a third (36.4%) of *all* the individual funds do not have a beta estimate statistically different from zero.

	MSCI Nordic	
	Average β	% of funds with β=0
Equities	**0.360**	30.6 %
Fixed Income	**0.165**	70.0 %
Multi Strategy	**0.267**	38.5 %
Managed Futures	**0.408**	50.0 %
FoHF	**0.282**	31.0 %
Total	**0.312**	36.4 %

Table 9.3: Statistics of the estimated stock-beta for the average individual Nordic hedge fund. Bold numbers indicate significance.

Figure 9.1 shows the distribution of beta estimates for all individual Nordic hedge funds, and appendix 9 shows the distribution of individual beta estimates within every hedge fund style. The distribution in figure 9.1 is very much centralized around 0.2-0.3 with a few extreme *positive* outliers. The beta distribution for Fixed Income range from -0.1 to 0.3 with 60% between 0.2-0.3. The distribution for Managed Futures is pretty much evenly distributed between -0.1 and 1.0, while the rest of the distributions are more or less centralized around 0.2-0.4. The extreme positive outliers from figure 9.1 can be attributed to the Equities style. All the distribution graphs more or less reflect the results in table 9.3.

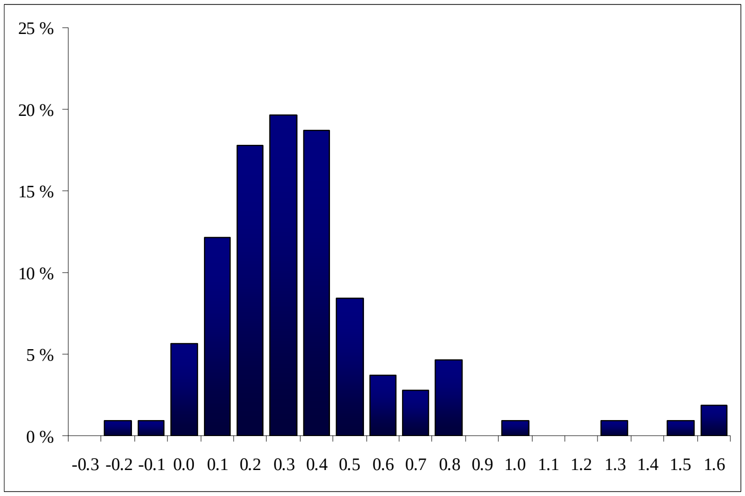

Figure 9.1: Distribution of beta for all individual hedge funds.

9.2.2. Bond market exposure

Table 9.1 showed that the Handelsbanken Nordic index had a statistical positive influence on all of the style indices. As with the stock market index MSCI Nordic, it may be interesting to split this bond index into country specific indices and see which ones that influence the different style indices the most. This is done in table 9.4 through a stepwise regression (to reduce the problem of collinearity).

According to table 9.4 the most influential bond market is the Swedish market. All indices except the Managed Futures have a positive loading against the Handelsbanken Sweden index. For Managed Futures the bond market with the most explanatory power is the Finnish market. The Danish bond market influences two of the indices, but with a negative loading. The Finnish index also has a negative impact on two of the hedge fund indices – the Equities and composite indices. Finally, the Norwegian bond market has a relatively small impact on the FoHF and composite indices. The sum of the coefficients for all hedge fund styles are close to that of the Handelsbanken Nordic index in table 9.1.

	Handelsbanken			
	Norway	Sweden	Denmark	Finland
Equities		1.183		-0.602
Fixed Income		1.010		
Multi Strategy		1.118	-0.328	
Managed Futures				1.340
FoHF	0.354	0.594	-0.747	
Composite	0.333	0.763		-0.488

Table 9.4: Loadings from a stepwise regression for the indices where the county specific Handelsbanken indices are the independent variables.

As for the stock market exposure, it may be interesting to see how the individual Nordic hedge funds are exposed to the Nordic bond markets. The middle column of table 9.5 shows the cross-sectional average individual beta coefficient within each hedge fund style. The beta coefficients now describe the loadings against the Handelsbanken Nordic index. As one can see, three averages are statistically different from zero. The funds within the Fixed Income style have the highest average beta, and this is not surprisingly since they operate in the fixed income market. The average for Multi Strategy and Managed Futures are also somewhat high, but the Multi Strategy is the only significant one. The reason why the Managed Futures average is not significant is the high dispersion of beta estimates which leads to a high standard error. Finally, the average bond-beta for *all* Nordic hedge funds is also statistically significant.

The last column of table 9.5 shows the percentage of individual funds within the style that have a beta estimate that is *not* statistically different from zero. For Fixed Income and Multi Strategy these percentages are relatively low and in accordance with the statistically significant cross-sectional average. Around 62% of all FoHF's have beta estimates around zero, and this explains the low cross-sectional average beta for this category. The rest of the styles contain around 43-50% of funds with statistically insignificant beta estimates. Just below half of all individual Nordic hedge funds exhibit beta around zero. As for the stock market exposure, this relatively high exposure to the bond market is not in line with the notion that hedge funds are market neutral (both to the stock and bond market).

	Handelsbanken Nordic	
	Average β	% of funds with β=0
Equities	0.153	42.9 %
Fixed Income	**1.327**	40.0 %
Multi Strategy	**0.548**	30.8 %
Managed Futures	0.644	50.0 %
FoHF	0.122	62.1 %
Total	**0.330**	46.7 %

Table 9.5: Statistics of the estimated bond-beta for the average individual Nordic hedge fund. Bold numbers indicate significance.

Figure 9.2 shows the distribution of beta estimates for all individual hedge funds. It is centralized around 0-1 with a few extreme negative and positive outliers. Over 50% of all beta estimates lie in the range 0.5-1. Appendix 10 exhibits the beta distribution for the five hedge fund styles. The distribution for Multi Strategy and Equities are very much centralized around 0.5-1 with a large portion in this interval. Equities also have some extreme negative outliers. The distribution of Fixed Income and Managed Futures are centralized slightly higher, while the distribution for FoHF's is centralized slightly lower.

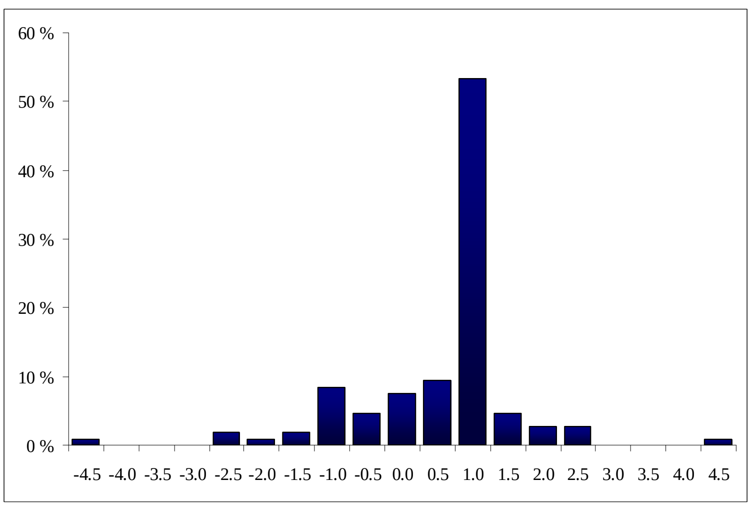

Figure 9.2: Distribution of bond-beta for all individual hedge funds.

9.3. Fund specific factors

The focus for the rest of this chapter will be on hedge fund specific factors that may influence returns. As mention earlier, a large portion of research has been conducted on this internationally, but none on Nordic funds in specific.

9.3.1. Assets under management

The first fund specific factor will be assets under management (AUM) or the size of the hedge fund. The AUM numbers are collected from Bloomberg and from the respective funds Internet pages. Still, only the AUM for 29 funds were available for this analysis. This sample size is ok in it self, but the question arises about whether the sample is random or if those funds that are willing to disclose their AUM have some hidden benefit from this. In addition, none of the dead funds were able to disclose their AUM, so these results may suffer from a survivorship bias.

To analyze the impact of AUM on hedge fund performance, the total sample of 29 funds is divided into four portfolios based on their *average* AUM for the whole sample period. The break points for these portfolios are chosen in accordance with Anjilvel et. al. (2000) and so that the number of funds in each portfolio is approximately the same. Then the equally-weighted return series for these portfolios are calculated, and based on this the annualized return, standard deviation and Sharpe ratio are estimated. The results are shown in table 9.6. The returns and standard deviations vary between 13-23% and 12-14%, respectively. The risk-adjusted relationship is represented with the Sharpe ratio[27] and the portfolio with the highest Sharpe is the funds with AUM between 10-50 million USD. There is no distinct pattern in these Sharpe ratios, but one may argue that the funds with AUM below 50 million USD seem to perform better than those with AUM above 50 million USD.

[27] The risk-free rate is set to 3.7% p.a. which is the annualized average for the sample period in question. This rate will be used for the entire chapter 9.3.

	Annualized			# funds
	Return	St.dev.	Sharpe	
AUM<10	18.25	12.92	1.13	6
10<=AUM<50	23.00	13.58	1.42	8
50<=AUM<200	13.13	11.93	0.79	8
AUM>=200	20.93	13.03	1.32	7

Table 9.6: Annualized return, standard deviation and Sharpe for four portfolios based on average AUM (in million US$).

The previous method may induce an endogenity problem since AUM also will be affected by the monthly returns and not just the other way around. To avoid this problem, an OLS regression between monthly returns and the AUM for the *previous* month are conducted. To reduce the problem of heteroscedasticity and to create a simple interpretation of the coefficient, the logarithmic transformation of AUM will be used as independent variable. In a log-log model the beta coefficient can be interpreted as a measure of elasticity. This means that a *one* percent increase in AUM will result in a *beta* percent increase in the returns. Model 1 in table 9.7 show the result from such an analysis. The beta coefficient is estimated to -0.144 and is statistically significant. This means that a one percent increase in AUM leads to a 0.144 percent *decrease* in monthly returns. This negative relationship is consistent with Brorsen and Harri (2004), and it may seem that small hedge funds outperform larger ones. The small funds are perhaps more capable of exploiting inefficiencies in the market.

Model 2 in table 9.7 tries to estimate the monthly returns by using two independent variables – ln(AUM) and ln(AUM) squared. This type of quadratic regression is a way of estimating the optimal amount of AUM. If the coefficient for ln(AUM) is significantly larger than zero and the coefficient for ln(AUM) squared is significantly lower than zero, then there will exist a positive and *concave* relationship with an optimal amount of AUM. This is however not the case here where none of the coefficients are significant and in addition the coefficients have the opposite signs. The relationship seems to be convex, but insignificant. These results are not in line with Getmansky (2004) and Ammann and Moerth (2005).

	Model 1	Model 2
ln(AUM)	**-0.144**	-1.131
ln(AUM)^2		0.028
Constant	**3.964**	12.648
R-squared	0.0043	0.0050

Table 9.7: Regression results between return and the logarithm of AUM (and AUM squared). Bold numbers indicate significance.

9.3.2. Age of fund

To test if there is a relationship between the age of the fund and performance, four portfolios based on age will be formed. These portfolios are equally-weighted and rebalance monthly. For the four age portfolios the annualized return, standard deviation and Sharpe will be estimated. The results are shown in table 9.8. Again the returns and standard deviations vary somewhat. So does the Sharpe ratios, but it may seem that there exist a positive relationship. Funds above 3 years have better Sharpe ratios than those funds whose age is less than 3 years. The optimal age seems to be between 3 and 5 years where the Sharpe ratio is the highest (1.58).

	Annualized			# funds
	Return	St.dev.	Sharpe	
Age<1	10.51	10.03	0.68	12
1<=Age<3	14.03	9.19	1.12	39
3<=Age<5	20.39	10.57	1.58	34
Age>=5	16.46	9.29	1.37	22

Table 9.8: Annualized return, standard deviation and Sharpe for four portfolios based on age.

9.3.3. Performance and management fees

To test the relationship between the two types of fees and performance, three portfolios are formed on the basis of performance and management fee, respectively. Again the portfolios are equally-weighted and rebalance monthly. Table 9.9 and 9.10 show the respective results. A performance fee of 20% seems to be the optimal fee. This may be explained by the fact that this fee structure creates an optimal balance between giving the manager the right incentives and at the same time not being too high for the investor to accept. When it comes to management fee, the optimal amount seems to be below 1%. This may also be explained by the same logic as for the performance fee. But this type of fee does not give the manager incentives to create returns above the hurdle rate, and therefore the investors will not accept high management fees.

	Annualized			# funds
	Return	St.dev.	Sharpe	
Perf.fee<20	13.90	11.04	0.92	28
Perf.fee=20	20.83	11.80	1.45	66
Perf.fee>20	12.13	12.14	0.69	3

Table 9.9: Annualized return, standard deviation and Sharpe for three portfolios based on performance fee.

	Annualized			# funds
	Return	St.dev.	Sharpe	
Mgmt.fee<1	22.21	14.79	1.25	16
Mgmt.fee=1	15.27	11.67	0.99	36
Mgmt.fee>1	13.00	8.61	1.08	45

Table 9.10: Annualized return, standard deviation and Sharpe for three portfolios based on management fee.

9.3.4. Investment universe

Table 9.11 uses the same portfolio formation technique as the previous sub-chapters, but now the portfolios are formed on the basis of the funds investment universe. Funds that can invest globally seem to outperform funds with a different investment universe. This does not come as a surprise since these funds have a larger variety of investment opportunities to select from. Many also believe that the amount of inefficiencies in the market is finite, and funds that have a smaller investment universe will probably also have less inefficiency to select from. The second best investment universe is the Nordic region. This may be explained by the notion that Nordic hedge funds have a deeper understanding for the Nordic markets and are therefore more capable of extracting inefficiencies from this market than other managers. The worst investment universe as measured by the Sharpe ratio is the Europe region.

	Annualized			# funds
	Return	St.dev.	Sharpe	
Global	18.56	11.22	1.32	40
Europe	11.31	12.37	0.62	7
Nordic	21.13	15.22	1.15	20
Sweden	14.40	10.86	0.99	9
Other	15.24	11.48	1.01	5

Table 9.11: Annualized return, standard deviation and Sharpe for five portfolios based on investment universe.

9.3.5. Use of high watermark

The use of high watermark prevents the hedge fund managers from extracting performance fees when they start to make money again after a losing period (they have to make up for the negative return before they can charge a performance fee again). This aligns the incentives for the managers and the investors, and one would expect that this affects the returns in a positive way. This is confirmed by the result of table 9.12 where the portfolio of funds with a high watermark clearly outperforms those without a high watermark.

	Annualized			# funds
	Return	St.dev.	Sharpe	
High Watermark	20.59	11.61	1.46	90
No High Watermark	11.65	10.77	0.74	9

Table 9.12: Annualized return, standard deviation and Sharpe for two portfolios based on the existence of a high watermark or not.

9.3.6. Subscription and redemption period

The subscription period describes how often one can *buy* shares in a hedge fund while the redemption period describes how often one can *sell* those shares. It is most common to have monthly or quarterly subscription and redemption periods, but some also have weekly or daily periods. Table 9.13 and 9.14 show the performance estimates for portfolios formed on the basis of subscription and redemption period, respectively. As one can see, funds with quarterly subscription and/or redemption period have outperformed the other funds. Monthly periods have also performed well. It may seem strange that funds where the investors relatively rarely can buy and/or sell their shares have done so much better. One would perhaps think that investors would prefer funds where they could get quickly in and (especially) out. One possible explanation for this outperformance may be the fact that longer periods give the managers more time to focus on investment decisions and not on cash management. The small sample of fund with weekly and daily periods may also be some of the explanation.

	Annualized			# funds
	Return	St.dev.	Sharpe	
Quarterly	19.74	11.52	1.39	11
Monthly	19.67	11.83	1.35	76
Weekly	5.11	8.13	0.17	3
Daily	11.73	10.88	0.74	7

Table 9.13: Annualized return, standard deviation and Sharpe for four portfolios based on the subscription period.

	Annualized			# funds
	Return	St.dev.	Sharpe	
Quarterly	25.61	14.41	1.52	29
Monthly	11.09	9.96	0.74	59
Weekly	5.11	8.13	0.17	3
Daily	11.73	10.88	0.74	7

Table 9.14: Annualized return, standard deviation and Sharpe for four portfolios based on the redemption period.

9.3.7. Country of registration

The final fund specific factor that will be examined in this chapter is the country of registration for the fund. Even though they operate from one country, they may be registered in another. Table 9.15 show the performance estimates for portfolios formed on the basis of country of registration. Not surprisingly, funds registered in tax paradises[28] seem to perform the best (although just slightly). Funds registered in Norway and Sweden also seem to perform well.

[28] Luxemburg, Cayman Island, Guernsey, Bahamas and Bermuda.

	Annualized			# funds
	Return	St.dev.	Sharpe	
Sweden	19.27	11.90	1.31	39
Finland	11.38	11.43	0.67	11
Norway	18.32	11.00	1.33	3
Ireland	15.10	10.06	1.13	10
Tax paradise	14.87	8.29	1.35	20
Denmark	4.27	9.13	0.06	1

Table 9.15: Annualized return, standard deviation and Sharpe for six portfolios based on country of registration.

10. Hedge Fund Return Replication

So far in this thesis, Nordic hedge funds have shown very good performance relative to other assets classes and American hedge funds. But hedge fund investing suffers from some drawbacks like liquidity, capacity and transparency problems in addition to high fees. This has lead to the development of hedge fund return replication strategies. Many researchers have shown that the returns of hedge funds can be replicated by investing in more liquid exchange-traded securities. Some of these approaches will be discussed in this chapter.

10.1. Alternative beta replication

This type of replication tries to mimic the hedge fund returns by using linear factor models with benchmark asset indices. Research has shown that hedge fund performance does not only depend on manager skills, but also on systematic exposure to "alternative beta" risk factors. The total hedge fund return can then be split up in the following way:

Hedge fund return = Traditional beta + Alternative beta + Alternative alpha

Agarwal and Naik (2000a) use an explicit macro-factor model in order to try to find alternative beta factors. They find that different hedge fund styles have significant exposure to different factors. For instance, the Event Driven and Equity Hedge styles exhibit loadings against an emerging market index (in addition to S&P 500 Composite). Other styles like the Restructuring index exhibit positive loadings against a high yield index and negative loadings against a government bond index. Other factors that influence American hedge funds are dollar and gold indices.

Similar studies for Nordic hedge funds are done in chapter 8.3, 8.4 and 9.2 of this thesis. Nordic hedge funds show significant loadings against alternative beta factors like small cap, crude oil, gold and the momentum effect of Jegadeesh and Titman (1993, 2001).

10.2. Option based replication

As documented in Fung and Hsieh (1997a), hedge fund managers typically employ dynamic trading strategies that have option-like returns. Linear factor models using standard asset benchmarks are not designed to capture these non-linear return features. To accommodate this, many researchers have started to include returns from option-like strategies in their factor models.

Fung and Hsieh (2001) use lookback straddles to model the return on trend-following hedge funds. They show that these types of option strategies can explain the returns better than standard asset class factors. The cost of implementing these strategies can be established using observable, exchange-traded option prices.

Agarwal and Naik (2004) find that a large number of equity-orientated hedge fund strategies exhibit payoffs resembling a short position in a put option on the market index. Their analysis consists of finding a portfolio of buy-and-hold and option-based risk factors that replicate the hedge fund returns (both individual and indices) in the best possible way in the in-sample period. Then they test the replication portfolio in the out-of-sample period. In addition they find that hedge funds exhibit significant risk exposure to Fama and French's (1993) size and value effect and Jegadeesh and Titman's (1993, 2001) momentum effect.

It was originally the plan to test these option-based strategies on Nordic hedge funds as well, but due to the difficulties of obtaining market prices for options on the Nordic stock index, this topic has been dropped from this thesis. It may be a subject for further research.

11. Persistency of Hedge Fund Performance

In this chapter the persistency of the performance for Nordic hedge funds will be examined. Is the good performance only due to luck, or does some funds continue to perform well? To clarify this question, several statistical tests will be conducted. These tests can be divided into *relative* persistency tests and *pure*, or absolute, persistency tests. The relative tests examines if there exits persistency in the rankings between the winners and losers, while the pure tests looks at the persistency of one fund at a time without considering other funds. Relative persistency tests can be conducted using a two-period framework or a multi-period framework.

11.1. Previous studies

The main three relative persistency tests in the two-period framework are the Cross Product Ratio (CPR) test, the Chi-square test and the Spearman rank correlation test. Agarwal and Naik (2000b) find significant persistence at 3 and 6 months horizons using a CPR test and a Chi-square test. The tests are conducted on US hedge funds from the HFR database in the period from 1982-1998. Using the same tests at 1 year horizons they find that the persistency is diminishing. Koh, Koh and Teo (2003) use the same two test on Asian hedge funds from 1999-2003 and find that persistency exist at 1 to 9 months horizons. At 1 and 2 year horizons, Caglayan and Edwards (2001b) find both winner and loser persistence using a CPR test on the MAR database from 1990-2001. Both Kat and Menexe (2003) and De Souza and Gokcan (2004) find no evidence of performance persistency at a 3 year horizon using a CPR test. Using a Chi-square test, Kouwenberg (2003) find some evidence of persistence at 2 year horizons, mainly for event driven, market neutral and global macro funds. Park and Staum (1998) use the Chi-square and the Spearman rank correlation test on the TASS database (1986-1997) and find that the persistency varies somewhat at 1 year horizons.

When it comes to the relative persistency tests in a multi-period framework, the main one is the Kolmogorov-Smirnov (K-S) test. It tests if the distribution of winning funds and losing funds are statistically different from a theoretical distribution. This type of test reduces the likelihood of finding persistent funds due to pure chance (because of a multi-period framework), and it is therefore considered to be the most powerful method for testing relative persistence (Géhin, 2006). Both Agarwal and Naik (2000b) and Koh, Koh and Teo (2003) find that using this test on longer than 6 month horizons, weakens the persistence.

To test the pure persistence of hedge fund performance, the Hurst exponent is used in combination with a D-statistic. A Hurst exponent close to 0 (1) indicates reverse (positive) persistence, while a Hurst exponent around 0.5 indicates that the returns follow a random walk. When the Hurst exponent is greater than 0.5, a D-statistic is estimated in order to determine whether positive or negative returns persist. The combination of a high Hurst exponent and a low D-statistic indicate the presence of pure *positive* return persistence. De Souza and Gokcan (2004) use this approach to test the pure persistence of individual hedge funds from the HFR database from 1997-2002. They find that funds with high Hurst exponent and low D-statistic outperform the other funds in the out-of-sample period. Gèhin (2005) also use the Hurst exponent and the D-statistic, but on hedge funds from the ACC database from 2000-2004 and with a Hurst exponent which must be greater than 0.6. The results are very much similar. The Hurst exponent appears to be a powerful indicator for analyzing the performance persistence of hedge funds.

11.2. Relative persistence

To test the relative persistence in the performance of Nordic hedge funds, the CPR and Chi-square test will be used. These tests are originally in the two-period framework, but to increase the power of the test the periods will be overlapping. This makes the tests a lightweight version of the more advanced multi-period tests like the Kolmogorov-Smirnov test. That is the reason why a K-S test will not be conducted in this thesis. A

Spearman rank correlation test will neither be conducted due to the fact that this test works best for a balanced panel dataset (which is not the case here).

To perform these two relative persistence tests, one needs to construct a so-called contingency table. This table shows the ranking frequency of funds over two consecutive periods. A fund is ranked as a WW if it is a winner in both periods, LL if it is a loser in both, and so on. How the fund is classified as a *winner/loser*, varies a lot in the previous research. The most common criteria are average return (De Souza and Gokcan, 2004), alpha (Agarwal and Naik (2000b), Caglayan and Edwards (2001b) and Kouwenberg (2003)), the appraisal ratio (Park and Straum (1998) and Agarwal and Naik (2000b)) and the Sharpe ratio (Kouwenberg (2003) and De Souza and Gokcan (2004)). In this thesis the alpha of Agarwal and Naik (2000b) and the standard Sharpe ratio will be used. A funds alpha at a point in time is estimated as its return less the average for all funds within the same style category. A fund is classified a winner (loser) at one time period if the estimated alpha or Sharpe is above (below) the median of *all* funds. The reason why two performance measures will be used instead of one is that they both have some weaknesses, but together the consequences of these weaknesses may be minimized. The alpha measure is sensitive to the use of leverage, while the Sharpe ratio may suffer from non-neglectable estimation error, especially at shorter horizons. The time periods used in the calculations are quarterly, half-yearly and yearly (all ending in December 2006).

Table 11.1 and 11.2 show the contingency tables based on alpha and Sharpe, respectively. The percentages range from roughly 20-30%. The percentages for WW and LL are higher than their respective WL and LW for the 3 and 6 months horizon. At the 1 year horizon the percentage of WW is quite small relative to WL, LW and LL. The fraction of consecutive losses (LL) is always higher than consecutive wins (WW). Under the null hypothesis of no persistence, these percentages should all be 25%. Statistical tests have to be conducted in order to make inference about this.

	WW	WL	LW	LL
3 month	26.3 %	23.4 %	23.1 %	27.2 %
6 month	26.8 %	22.5 %	21.1 %	29.6 %
1 year	20.0 %	28.1 %	23.3 %	28.6 %

Table 11.1: Contingency table showing the percentages of WW, WL, LW and LL when alpha is used as a performance measure.

	WW	WL	LW	LL
3 month	26.2 %	23.4 %	23.1 %	27.2 %
6 month	27.1 %	22.5 %	21.5 %	28.9 %
1 year	21.9 %	26.2 %	24.3 %	27.6 %

Table 11.2: Contingency table showing the percentages of WW, WL, LW and LL when the Sharpe ratio is used as a performance measure.

The CPR is calculated in the following way:

$$CPR = \frac{WW \times LL}{WL \times LW} \tag{11.1}$$

Under the null, this ratio should be equal to 1. To test the significance of this ratio a Z-statistic is calculated as in (11.2). The standard error to the natural logarithm of the ratio is estimated with (11.3).

$$Z - statistic = \frac{\ln(CPR)}{SE(\ln(CPR))} \tag{11.2}$$

$$SE(\ln(CPR)) = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}} \tag{11.3}$$

The Chi-square test is carried out by comparing the distribution of the observed frequencies of WW, WL, LW and LL with the expected frequencies of the distribution. The test statistic is calculated as in (11.4).

$$\chi^2 = \frac{(WW - D1)^2}{D1} + \frac{(WL - D2)^2}{D2} + \frac{(LW - D3)^2}{D3} + \frac{(LL - D4)^2}{D4} \tag{11.4}$$

Where:

$$D1 = \frac{(WW + WL) \times (WW + LW)}{N} \quad , \quad D2 = \frac{(WW + WL) \times (WL + LL)}{N} \quad ,$$

$$D3 = \frac{(LW + LL) \times (WW + LW)}{N} \quad , \quad D4 = \frac{(LW + LL) \times (WL + LL)}{N} \quad \text{, and}$$

$$N = WW + WL + LW + LL$$

The Chi-square statistic follows the chi-square distribution with one degree of freedom. Carpenter and Lynch (1999) argue that the Chi-square test is more robust than the CPR test when survivorship bias is present.

The results from the CPR and Chi-square tests based on alpha and the Sharpe ratio are presented in table 11.3 and 11.4, respectively. First of all, the consistency between the two tests for each performance measure indicates that the consequences of the survivorship bias may not be that severe (it may even be non-existing). The tests produce almost identical p-values. Furthermore, the tables show that the performance persistency is statistically significant at the 3 and 6 months horizons for both tests and performance measures. At the 1 year horizon, neither tests yield significant results.

	CPR	Z-statistic	P-value	Chi-square	P-value
3 month	1.33	2.55	0.0107	6.54	0.0106
6 month	1.66	3.00	0.0028	9.06	0.0026
1 year	0.87	-0.49	0.6230	0.24	0.6224

Table 11.3: Results of the CPR and Chi-square tests when alpha is used as the performance measure.

	CPR	Z-statistic	P-value	Chi-square	P-value
3 month	1.32	2.50	0.0126	6.25	0.0124
6 month	1.62	2.84	0.0046	8.12	0.0044
1 year	0.95	-0.18	0.8568	0.03	0.8566

Table 11.4: Results of the CPR and Chi-square tests when the Sharpe ratio is used as the performance measure.

11.3. Pure persistence

Unlike the relative persistence tests, the pure persistence tests allow the funds that exhibit the strongest persistency in their own returns to be identified fund by fund. To test the pure persistence of hedge fund returns the Hurst exponent in combination with the D-statistic will be used. The advantage of using the Hurst exponent is that it is not dependent on any assumption about the return distribution. It only measures weather a positive or negative trend persists or mean reverts. The Hurst exponent is estimated via (11.5) where R is the range of cumulative deviations from the mean return (monthly), and σ is the (monthly) standard deviation of the returns.

$$H_i = \frac{\ln\left(\frac{R_i}{\sigma_i}\right)}{\ln\left(\frac{N_i}{2}\right)} \tag{11.5}$$

N is the number of monthly returns. The Hurst exponent only indicates if the returns persist, not if the persistency is in negative or positive returns. To identify the funds with a high Hurst exponent and a *positive* persistence, a D-statistic for each fund is calculated as in (11.6).

$$D - statistic = \frac{\sum_t |negative\_returns|}{\sum_t |all\_returns|} \tag{11.6}$$

The approach in this thesis is the same as used in Gèhin (2005) where the total sample is split into two sub-samples – one in-sample and one out-of-sample. First the Hurst exponents and the D-statistics are estimated for all individual hedge funds with more than 18 months of history as of December 2006 (20 funds excluded). This is done for the in-sample period which in this thesis is set to be July 1996 to December 2005. The result of these in-sample estimations are presented in table 11.5. The minimum Hurst exponent is

0.501 while the maximum is 0.825, both somewhat higher than Gèhin (2005). For a fund to have a significant *positive* persistence in the returns it needs to have a Hurst exponent greater than 0.6 and a D-statistic less than 0.3 (in accordance with Gèhin (2005)). There are 24 funds, or 27.6%, that satisfy these conditions. This is almost identical to Gèhin (2005).

	Min. Hurst	Max. Hurst	Positive persistence of positive returns (Hurst > 0.6 and D < 0.3)	
			Number of funds	%
Jan. 1996 - Dec. 2005	0.501	0.825	24	27.6 %

Table 11.5: Results from the in-sample estimations of the Hurst exponent.

After the in-sample estimations an out-of-sample test is conducted to see if the funds which were identified as having positive persistence will continue to persist. This is done by estimating the annualized Sharpe ratio for an equally-weighted portfolio of persistent funds and for the rest of the funds. The results are shown in table 11.6. The average monthly return for the persistent portfolio is 1.46% while it is 1.68% for the other funds. But the monthly standard deviation is substantially lower for the persistent portfolio with 1.91% versus 2.72%. This leads to a Sharpe ratio of 2.21 for the persistent funds while the ratio is only 1.84 for the rest of the funds. These results may be interpreted in the way that selecting funds on the basis of the Hurst exponent and the D-statistic allows persistent funds to be isolated.

	Average monthly return	Monthly st.dev.	Annualized Sharpe ratio
Persistent funds	1.46	1.91	2.21
Other funds	1.68	2.72	1.84

Table 11.6: Results from the out-of-sample estimation of performance for the two portfolios with persistent funds and for all the other funds. The risk-free rate in the Sharpe ratio is set to the 2006 average of 0.24% per month.

11.4. Return on the momentum portfolio

One final way of testing for persistence in hedge fund returns is to test if the momentum portfolio of Jegadeesh and Titman (1993, 2001) yields significantly positive return. In their papers they find that forming portfolios of past 3-12 months performance (long outperformers and short underperformers) yields a significant positive return in the holding period (also ranging from 3 to 12 months). In this thesis 10 equally-weighted portfolios will be formed on the basis of individual funds performance during the past 6 months. Then the return for these portfolios will be estimated for the next 3, 6 and 12 months (the holding period). The return on the momentum portfolio is then the difference between the return on the portfolios of the past outperformers and the past underperformers. Due to the fact that the sample of Nordic hedge funds is relatively thin in the early years and that 10 portfolios will be formed, this momentum test is only performed on a sub-sample which is from January 2003 to December 2006. To increase the power of the test, overlapping estimation windows will be used.

The return on the momentum portfolios with different holding periods are presented in table 11.7. The monthly returns for all three portfolios are around 0.9-1% and highly statistically different from zero. This is a strong indication that persistence is present for Nordic hedge funds.

	Holding period		
	3 months	6 months	1 year
Mean	0.98	1.04	0.88
St.dev	1.66	1.02	0.52
T-statistic	3.73	6.20	9.43
P-value	0.0006	0.0000	0.0000

Table 11.7: Return on the momentum portfolios with different holding periods.

12. The Influence of Currency on the Results

As explained in chapter 4.1, all the numbers in this thesis have been converted into US dollars in order to be able to compare the performance of funds with different base currencies. The consequence of this is that the conclusions reached are from a US investor's viewpoint. But all the analyses in this thesis have also been conducted in local currencies, and the differences between these two approaches will be briefly presented in this chapter.

The descriptive statistics in chapter 5 were somewhat different when they were conducted in local currency. First of all, the means, standard deviations and skewness' were on average a bit lower while the excess kurtoses did not change much. The fractions of individual funds with normally distributed returns were also a bit higher.

The correlations in chapter 6 were also different for local currency. The correlation to the Handelsbanken Nordic and MSCI Nordic were on average lower. The average individual fund's correlation in bull markets was also lower, while the opposite was the case for bear markets. The asymmetric correlations are in other words worse for the local currency case. The correlation between individual hedge funds was substantially lower when calculated on local currency, meaning that the diversification benefits between individual hedge funds are greater in local currencies.

The performance measurements in chapter 7 did not change very much. They only small difference was that the distance between the measures for hedge funds and traditional asset classes were reduced slightly when going from local currency to USD.

Three of the asset pricing models in chapter 8 experienced different results when they were tested on USD returns. In local currency all models failed pretty clear, but when the returns were transformed into USD, three of the models produced insignificant alphas on average for individual funds. These models were the adjusted CAPM, the Four factor model and the Explicit macro-factor model.

For chapter 9, the exposure to the Nordic bond and stock market was more apparent when the analyses were conducted in USD than in local currency.

Finally, the persistence results from chapter 11 only changed slightly. The persistence was clearer at the 3 months horizon when the analyses were performed on USD returns. In addition, the persistence was clearly rejected at 1 year horizon (for USD returns).

13. Possible Bias in this Thesis

Before the concluding remarks for this thesis, it is important to comment on some of the possible bias' that may affect the results presented.

First of all, the self-selection bias presented in chapter 4.2.1 may affect the results. Nordic hedge funds are not forced to disclose their performance data to the HedgeNordic database. This may lead young hedge funds and funds that have performed badly in the past not to join the database. As a result, the conclusions presented here may overestimate the true performance of Nordic hedge funds.

The sample selection bias presented in chapter 4.2.4 may also create a performance bias. As mention earlier in this paper, the HedgeNordic database is not a complete list of all Nordic hedge funds. Although most of the funds in the Nordic region are in this database, the sample used in this thesis can not be regarded as a completely random sample (which is required to be able to make inference about the entire population of Nordic hedge funds).

Also the last bias presented in chapter 4.2, the illiquidity bias, may affect the results presented here. This bias is a result of the fact that hedge fund managers have the ability to "manage" their net asset value (mostly due to difficult to value securities). Autocorrelation in the return series may be an indication of the importance of this bias. Chapter 5.2 shows that autocorrelation is mostly present in the styles Equities and Managed Futures. Funds within these styles *may* therefore suffer from this type of bias. But the consequences of this bias is thought to be minimal since only 10.2% of the funds in the Equities style suffer from significant first order autocorrelation (and this style is by far the largest category).

In chapter 7 and 8 the MSCI World and MSCI Nordic indices are used as a proxy for the market portfolio. The choice of these indices as proxy may influence the results. But this bias will always be there since it is impossible to use the correct (theoretical) market portfolio. However, chapter 9.2 shows that most of the Nordic hedge funds mainly have beta loadings against the MSCI Nordic index. This may indicate that this index could serve as a good proxy for the market portfolio for Nordic hedge funds.

In chapter 9.3 different fund specific data are used. The quality of these data may also affect the results in this thesis. The results may for example be sensitive to the investment universe classifications that the funds themselves provide. They may be classified as a global fund when they perhaps mainly is investing in the Nordic countries and therefore should be classified as a Nordic fund in this thesis. But the consequence of this bias is thought to be minimal. In addition, several of these fund specific factors *may* have been changed over time. This would also have an affect on the results.

14. Concluding Remarks

The first topic that is covered in this thesis is the statistical properties of hedge funds. For Nordic hedge funds these properties look very good. The mean/variance relationship is much like previous studies. But the skewness is higher (and even positive) and the excess kurtosis is substantially lower than previous studies. This is all favorable for Nordic hedge funds. There are also evidence pointing in the direction of some significant positive autocorrelation and non-normality in the return distributions. For American hedge fund indices the results are somewhat different. They have lower means, standard deviations and skewness', higher excess kurtoses, and more autocorrelation. This is more in line with previous international studies.

The correlations between hedge funds and the stock and bond markets are in general low. The average individual correlations with the stock markets are around 0.2-0.4 while it is closer to zero for the bond markets. The correlations are the highest against the MSCI Nordic and Handelsbanken Nordic indices. In a bull market, the correlations with the stock markets are mostly lower, while the correlations to the bond markets are somewhat higher (except for the Handelsbanken Nordic index). In bear markets the correlations to the stock markets decrease substantially and even become negative for some styles. The correlations to the bond markets mostly increase. This is a good thing for Nordic hedge funds. During a financial crisis the correlations to both the stock and bond markets vary a lot. Fund of hedge funds have a very high correlation to the stock markets. Fixed Income and Managed Futures have a high negative correlation to the stock markets while they have a high positive correlation to the bond markets. The average individual Equities hedge fund also has a negative correlation to the stock markets and a high correlation to the bond markets. The correlations between the American hedge funds and the stock and bond markets are in general higher and less favorable than their Nordic counterparts. The correlations between individual Nordic hedge funds range from around 0.11-0.65 and the optimal number of hedge funds in a portfolio is estimated to be around 17-18.

The overall conclusion when it comes to performance measurement for hedge funds is very clear. They outperform most of the stock, bond and commodity indices even after adjusting for the fact that hedge funds exhibit some positive autocorrelation and non-neglectable higher moments. The choice of performance measure is very important for all groups of assets except for stocks. The average Spearman's rank correlation coefficient between the different performance measures for stocks is relatively high, while the opposite is true for hedge funds, bonds and commodities. The choice of performance measure should be based on the existence of either autocorrelation, skewness and/or excess kurtosis in the returns.

In chapter 8, five asset pricing models are used to see if they can describe the returns of Nordic hedge funds. None of the models seem to describe the returns on the composite index since they all produce significant alphas. For three of the models (the adjusted CAPM, the Four factor model and the Explicit macro-factor model), on the other hand, I could not reject the hypothesis that the average individual alpha is different from zero. They therefore seem to describe the individual returns well.

Chapter 9 focus on the sources of hedge fund return and risk. Most of the style indices have significant positive exposure to the MSCI Nordic index. Only the Managed Futures index has no exposure to any of the stock market indices, while the Fund of hedge fund style only has exposure to the MSCI World Small Cap index. The average individual stock market betas are significantly different from zero for all styles. The indices exposure to the bond market is even clearer. All the style indices have positive loadings against the Handelsbanken Nordic index. Two of the styles (Fixed Income and Multi Strategy) have a significant average individual beta. This is also true for the total average of all funds bond market beta. These results mean that some of the good performance of the hedge funds can be attributed to general stock and bond market risk.

Some fund specific factors seems to influence the hedge fund returns. Assets under management (AUM) seem to have a negative impact on returns. Smaller funds outperform larger funds on average. Funds that are older than 3 years seem to perform better than those who are younger than 3 years. The optimal fee structure seems to be a 20% performance fee and a management fee that is lower than 1%. Funds with a global investment universe seem to outperform all other funds, while the use of high watermark clearly enhances the performance. The optimal subscription and redemption period seems to be either monthly or quarterly. Finally, funds that are registered in tax paradises seem to outperform other funds. But funds registered in Norway or Sweden only perform slightly worse.

The final topic that is covered in this thesis is the persistence of hedge fund returns. The relative persistency tests indicate persistence at 3 and 6 month horizons, but not at 1 year horizon. Using the Hurst exponent and a D-statistic is a good way of isolating funds that have a positive persistence. The momentum portfolio based on the previous 6 month return for hedge funds yield a statistically significant positive return of around 1% per month in the holding period (3-12 months). This is a clear indication that there exists persistence in hedge fund returns.

The overall conclusion for this closer study of Nordic hedge funds is very clear. They perform very well both compared to American hedge funds and the general stock and bond markets. The correlations to these markets are low. The risk-adjusted performance for hedge funds is pretty good, but some of the good performance may be attributed to general stock and bond market exposure. Some persistency in hedge fund returns is also present at shorter horizons.

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Appendices

Appendix 1

This appendix shows the annualized performance measurements for hedge funds and stock, bond and commodity indices. To estimate the modified Sharpe ratios the 95% VaR is used. The MAR and thresholds in the Sortino ratio, the Omega and the Kappa is set to zero for simplicity, and n=3 in the Kappa measure.

	Sharpe	Treynor	Jensens Alpha	AR-adjusted SR	Modified SR	Sortino	Omega	Kappa	N
Panel A: Average individual hedge fund (Nordic)									
Equities	1.09	-9.32	13.37	1.51	0.54	2.21	3.63	2.94	46
Fixed Income	0.75	266.05	7.83	0.45	0.35	1.39	2.42	1.91	9
Multi Strategy	0.94	760.21	9.15	1.13	0.44	2.25	3.59	2.86	11
Managed Futures	0.62	23.73	10.03	0.78	0.33	1.00	1.94	1.35	6
FoHF	0.63	56.28	5.33	0.90	0.36	1.66	2.66	2.25	0
Total	0.89	129.54	9.97	1.17	0.45	1.92	3.16	2.55	72
Panel B: Hedge fund indices (Nordic)									
Equities	1.41	84.94	19.94	1.16	0.67	2.19	3.75	2.60	126
Fixed Income	0.91	143.84	10.34	0.94	0.44	1.45	2.40	1.93	69
Multy Strategy	0.95	45.40	9.16	1.11	0.45	1.52	2.58	1.99	108
Managed Futures	0.96	1089.62	15.63	0.99	0.54	1.76	2.50	2.31	80
FoHF	0.87	29.67	7.98	0.98	0.46	1.57	2.66	1.92	126
Composite	1.45	65.10	13.22	1.53	0.70	2.81	3.95	3.76	126
Panel C: Hedge fund indices (American)									
HFRI Convertible Arbitrage Index	1.54	87.98	5.12	0.99	0.52	2.19	6.02	2.71	126
HFRI Distressed Securities Index	1.42	39.94	7.29	1.09	0.42	1.62	5.26	1.66	126
HFRI Emerging Markets (Total)	0.60	12.84	7.20	0.45	0.22	0.71	1.91	0.80	126
HFRI Equity Hedge Index	0.99	19.40	7.99	0.80	0.47	1.65	2.95	2.01	126
HFRI Equity Market Neutral Index	1.12	110.61	3.35	0.83	0.49	2.86	6.58	3.62	126
HFRI Equity Non-Hedge Index	0.59	10.19	6.51	0.61	0.27	0.85	1.83	1.05	126
HFRI Event-Driven Index	1.27	25.45	7.46	1.11	0.42	1.60	3.96	1.71	126
HFRI Fixed Income (Total)	1.23	40.35	3.59	1.11	0.39	1.76	5.84	2.08	126
HFRI Macro Index	0.91	29.99	5.46	1.12	0.46	1.94	3.18	2.44	126
HFRI Market Timing Index	1.12	22.54	7.53	1.01	0.52	2.16	3.15	2.88	126
HFRI Merger Arbitrage Index	1.35	36.71	4.78	0.91	0.40	1.67	5.30	1.81	126
HFRI Regulation D Index	1.37	60.56	9.28	0.80	0.67	2.51	4.25	3.33	126
HFRI Relative Value Arbitrage Index	1.70	52.54	5.13	1.35	0.41	1.74	9.17	1.72	126
HFRI Short Selling Index	0.00	0.02	2.50	0.00	0.00	0.20	1.16	0.23	126
HFRI Fund of Funds Composite Index	0.71	16.85	3.61	0.58	0.28	1.43	2.91	1.51	126
HFRI Fund Weighted Composite Index	0.94	17.53	5.87	0.84	0.36	1.46	2.98	1.63	126
Panel D: Stock indices									
MSCI World	0.17	2.41	0.00	0.15	0.07	0.37	1.36	0.46	126
MSCI US	0.21	3.27	0.89	0.19	0.10	0.42	1.39	0.52	126
MSCI Europe	0.31	4.95	2.54	0.27	0.14	0.49	1.50	0.60	126
MSCI Nordic	0.35	6.15	5.22	0.29	0.17	0.48	1.45	0.60	126
MSCI World Small Cap	0.27	4.83	2.25	0.26	0.12	0.48	1.44	0.57	126
MSCI US Small Cap	0.34	6.23	3.86	0.39	0.16	0.50	1.50	0.62	126
MSCI Europe Small Cap	0.44	8.53	5.27	0.38	0.18	0.60	1.64	0.70	126
MSCI Nordic Small Cap	0.61	11.87	8.92	0.51	0.25	0.71	1.82	0.84	126
Panel E: Bond indices									
Lehman Global	-1.32	169.23	-3.84	-1.25	-0.67	-0.05	0.96	-0.06	126
Lehman US Gov.	-0.88	66.32	-3.66	-1.04	-0.42	-0.01	0.99	-0.02	126
Lehman US High Yield	-0.18	-6.20	-2.92	-0.20	-0.09	0.14	1.13	0.17	120
Handelsbanken Nordic	-0.44	-1405.32	-3.93	-0.35	-0.28	-0.02	0.98	-0.03	126
Panel F: Commodities									
Bloomberg European Commodity index	0.20	29.51	2.99	0.16	0.10	0.42	1.37	0.53	126
IPE Brent Crude	0.42	-315.17	14.30	0.50	0.20	0.50	1.45	0.65	102
Englehard Gold Bullion Spot	0.08	14.49	0.98	0.08	0.05	0.41	1.30	0.55	126
MSCI Energy	0.42	10.63	5.66	0.50	0.22	0.71	1.61	0.90	126
LME Aluminium	0.14	5.92	1.29	0.14	0.09	0.46	1.34	0.60	126
LME Copper	0.34	14.81	6.30	0.27	0.22	0.65	1.47	0.85	126
Natural Gas NY	0.03	-31.78	2.95	0.05	0.01	0.07	1.06	0.08	126

Appendix 2

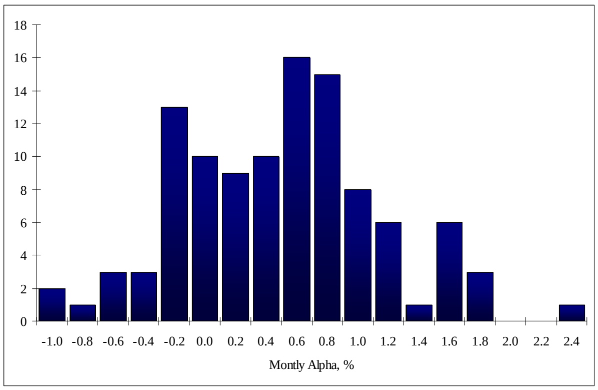
This appendix shows the Spearman's rank correlation coefficients between the different performance measures.

	Treynor	Jensens Alpha	AR-adjusted SR	Modified SR	Sortino	Omega	Kappa
Panel A: Average individual hedge fund (Nordic)							
Sharpe	0.09	0.37	0.77	0.89	0.89	0.94	0.94
Treynor		-0.60	-0.31	-0.14	0.26	-0.03	-0.03
Jensens Alpha			0.54	0.37	0.14	0.31	0.31
AR-adjusted SR				0.94	0.77	0.89	0.89
Modified SR					0.83	0.94	0.94
Sortino						0.94	0.94
Omega							1.00
Panel B: Hedge fund indices (Nordic)							
Sharpe	0.31	0.77	0.89	0.83	0.83	0.60	1.00
Treynor		0.71	-0.14	0.03	0.03	-0.49	0.31
Jensens Alpha			0.49	0.60	0.60	0.20	0.77
AR-adjusted SR				0.83	0.83	0.83	0.89
Modified SR					1.00	0.83	0.83
Sortino						0.83	0.83
Omega							0.60
Panel C: Hedge fund indices (American)							
Sharpe	0.82	0.19	0.65	0.62	0.62	0.86	0.54
Treynor		-0.06	0.56	0.72	0.88	0.95	0.80
Jensens Alpha			0.09	0.44	0.06	-0.18	0.14
AR-adjusted SR				0.41	0.48	0.68	0.43
Modified SR					0.88	0.55	0.90
Sortino						0.76	0.98
Omega							0.67
Panel D: Stock indices							
Sharpe	0.98	1.00	0.93	1.00	0.93	0.90	0.93
Treynor		0.98	0.98	0.98	0.98	0.93	0.98
Jensens Alpha			0.93	1.00	0.93	0.90	0.93
AR-adjusted SR				0.93	0.95	0.88	0.95
Modified SR					0.93	0.90	0.93
Sortino						0.98	1.00
Omega							0.98
Panel E: Bonds							
Sharpe	-0.80	0.40	1.00	1.00	0.80	0.80	0.80
Treynor		0.20	-0.80	-0.80	-0.40	-0.40	-0.40
Jensens Alpha			0.40	0.40	0.80	0.80	0.80
AR-adjusted SR				1.00	0.80	0.80	0.80
Modified SR					0.80	0.80	0.80
Sortino						1.00	1.00
Omega							1.00
Panel F: Commodities							
Sharpe	0.04	0.79	1.00	0.96	0.93	0.96	0.86
Treynor		-0.14	0.04	0.21	0.07	0.21	0.00
Jensens Alpha			0.79	0.75	0.68	0.75	0.57
AR-adjusted SR				0.96	0.93	0.96	0.86
Modified SR					0.96	1.00	0.89
Sortino						0.96	0.96
Omega							0.89

Appendix 3

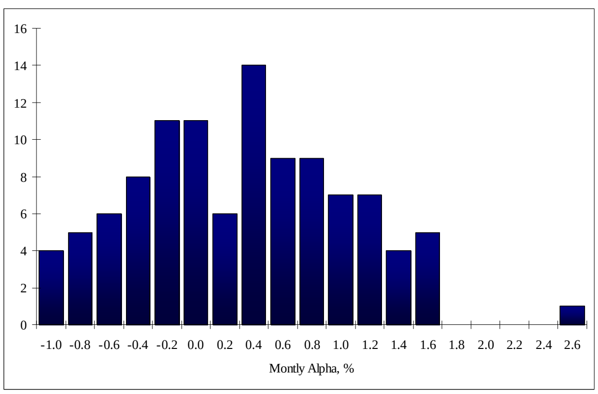
Distributions under different proxies for the market portfolio in the CAPM.

MSCI Nordic:



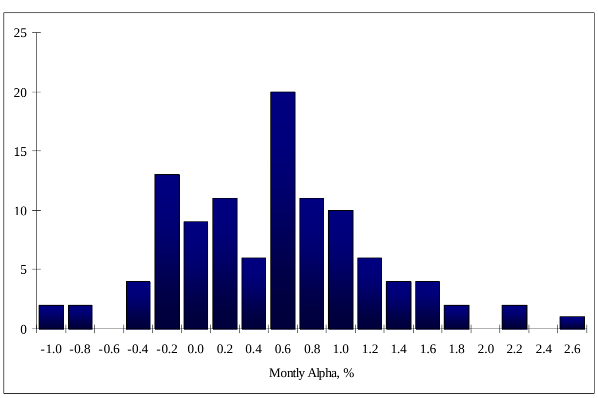
Mean	0.39
St.dev.	0.65
Skewness	0.17
Excess kurtosis	-2.75
N	107
Jarque-Bera	34.12
P(J-B)	0.0000

MSCI Europe:



Mean	0.19
St.dev.	0.78
Skewness	-0.25
Excess kurtosis	-2.28
N	107
Jarque-Bera	24.32
P(J-B)	0.0000

MSCI World:

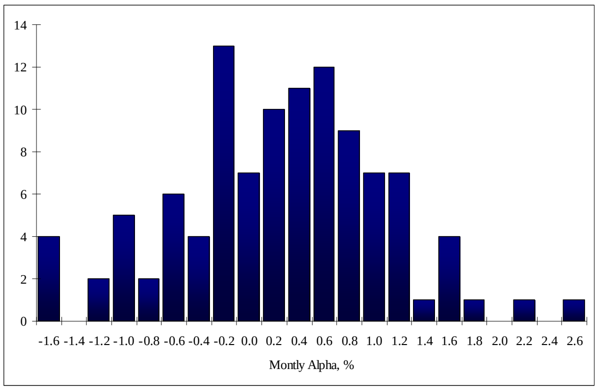


Mean	0.45
St.dev.	0.68
Skewness	0.23
Excess kurtosis	-2.54
N	107
Jarque-Bera	29.73
P(J-B)	0.0000

Appendix 4

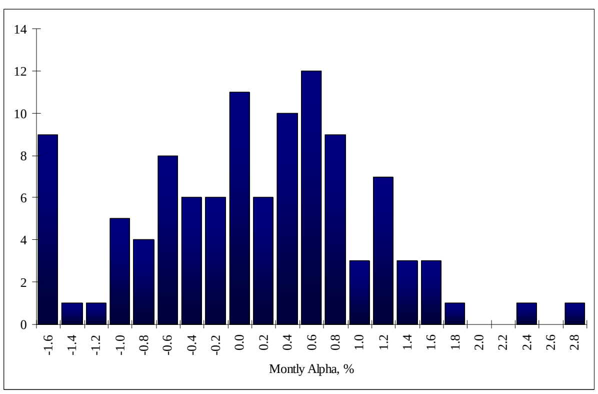
Distributions under different proxies for the market portfolio in the adjusted CAPM.

MSCI Nordic:



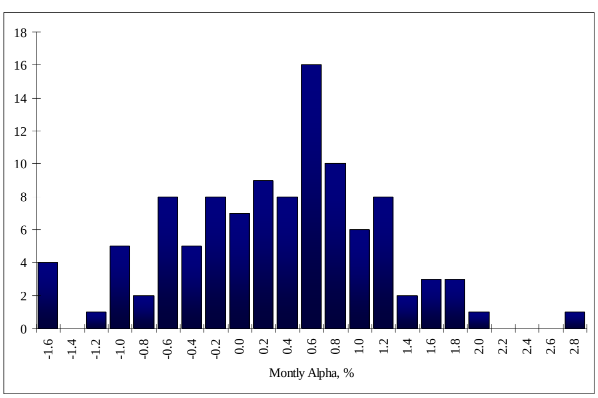
Mean	0.14
St.dev.	0.88
Skewness	-0.42
Excess kurtosis	-2.14
N	107
Jarque-Bera	23.55
P(J-B)	0.0000

MSCI Europe:



Mean	-0.04
St.dev.	1.12
Skewness	-0.87
Excess kurtosis	-0.97
N	107
Jarque-Bera	17.81
P(J-B)	0.0001

MSCI World:

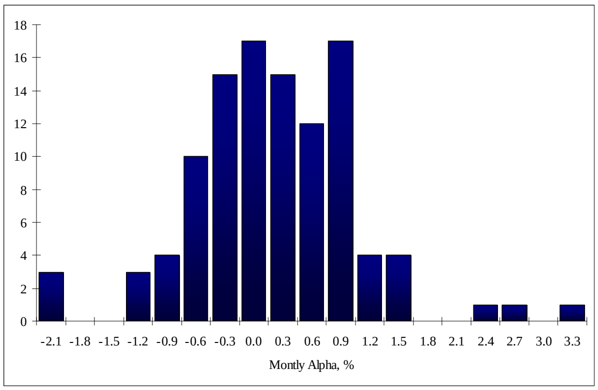


Mean	0.19
St.dev.	0.86
Skewness	-0.21
Excess kurtosis	-2.68
N	107
Jarque-Bera	32.77
P(J-B)	0.0000

Appendix 5

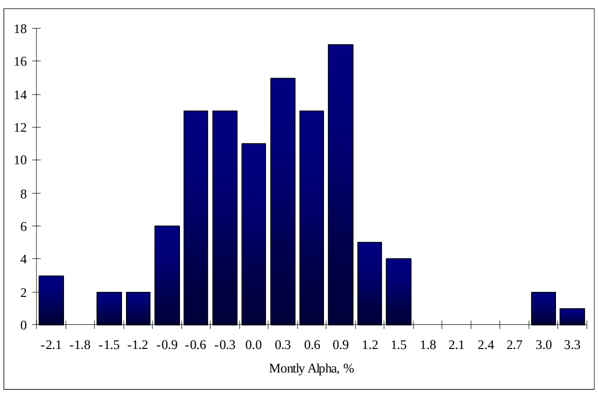
Distributions under different proxies for the market portfolio in the Four Factor Model.

MSCI Nordic:



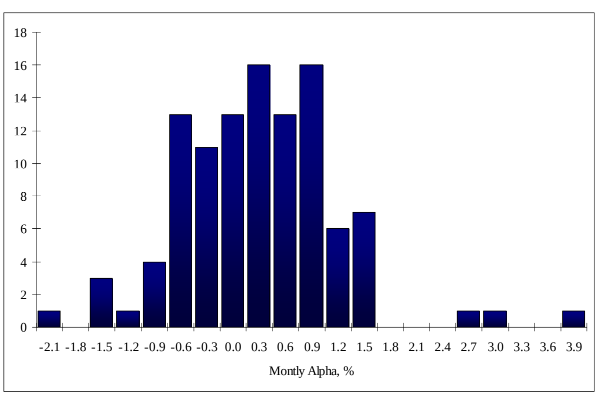
Mean	0.04
St.dev.	0.94
Skewness	-0.57
Excess kurtosis	1.22
N	107
Jarque-Bera	12.45
P(J-B)	0.0020

MSCI Europe:



Mean	0.03
St.dev.	0.98
Skewness	-0.32
Excess kurtosis	0.82
N	107
Jarque-Bera	4.87
P(J-B)	0.0875

MSCI World:



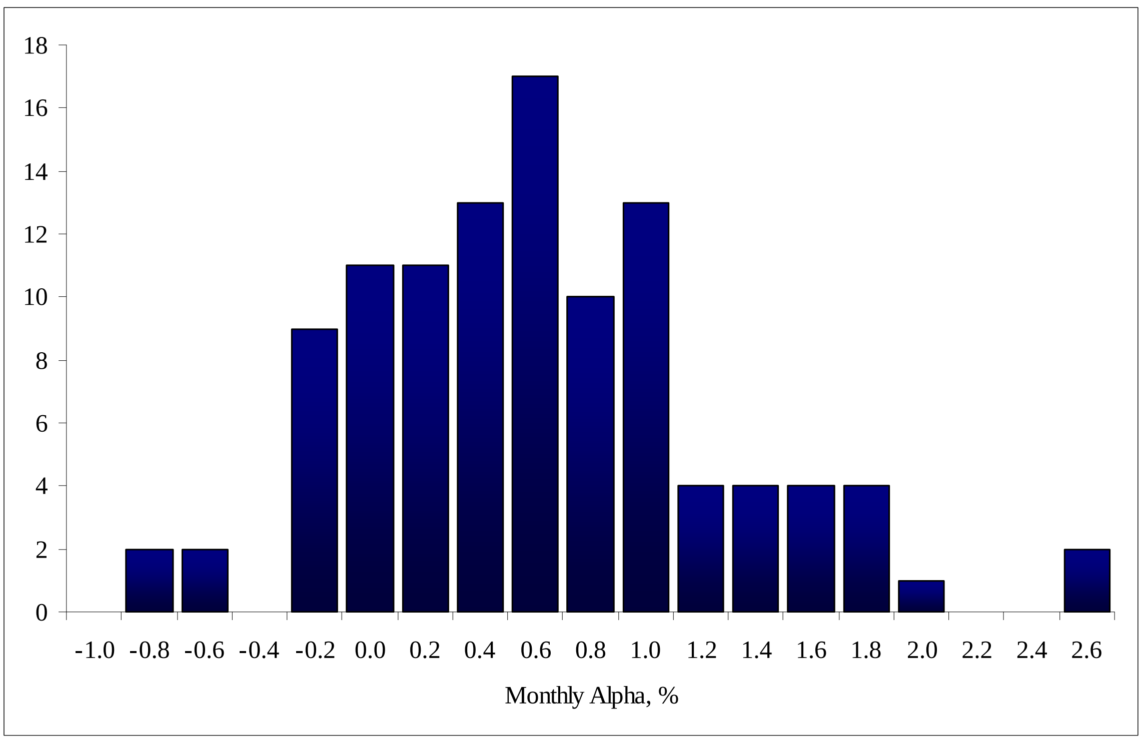
Mean	0.13
St.dev.	0.95
Skewness	-0.04
Excess kurtosis	0.74
N	107
Jarque-Bera	2.48
P(J-B)	0.2899

Appendix 6

Estimation results when a principal component analyses is used to estimate the proxy for the market portfolio (used to test the CAPM). Standard errors are reported in parentheses.

	Composite Index	Average individual fund
Alpha (monthly), %	1.14	0.51
Std. Error Alpha (monthly), %	(0.22)	(0.06)
P-value (for Alpha not 0)	0.0000	0.0000
R-squared	0.1926	
Percent of funds with Alpha significant > 0	31.8 %	
Percent of funds with Alpha significant < 0	0.0 %	

Distribution of the alphas:



Appendix 7

This appendix shows the estimates of alphas for different principal components in the implicit factor models (standard errors are reported in parentheses).

Alphas when the principal components (3) are formed from the 21 hedge funds that were registered in HedgeNordic as of January 2002:

	Composite Index	Average individual fund
Alpha (monthly), %	1.10	1.01
Std. Error Alpha (monthly), %	(0.05)	(0.06)
P-value (for Alpha not 0)	0.0000	0.0000
R-squared	0.9834	
Percent of funds with Alpha significant > 0	79.4 %	
Percent of funds with Alpha significant < 0	0.0 %	

Alphas when the principal components (4) are formed from the 33 hedge funds that were registered in HedgeNordic as of January 2003:

	Composite Index	Average individual fund
Alpha (monthly), %	1.02	0.97
Std. Error Alpha (monthly), %	(0.03)	(0.06)
P-value (for Alpha not 0)	0.0000	0.0000
R-squared	0.9940	
Percent of funds with Alpha significant > 0	76.6 %	
Percent of funds with Alpha significant < 0	0.0 %	

Alphas when the principal components (4) are formed from the 54 hedge funds that were registered in HedgeNordic as of January 2004:

	Composite Index	Average individual fund
Alpha (monthly), %	0.65	0.61
Std. Error Alpha (monthly), %	(0.02)	(0.07)
P-value (for Alpha not 0)	0.0000	0.0000
R-squared	0.9976	
Percent of funds with Alpha significant > 0	62.6 %	
Percent of funds with Alpha significant < 0	0.9 %	

Alphas when the principal components (7) are formed from the 66 hedge funds that were registered in HedgeNordic as of January 2005:

	Composite Index	Average individual fund
Alpha (monthly), %	0.46	0.46
Std. Error Alpha (monthly), %	(0.03)	(0.08)
P-value (for Alpha not 0)	0.0000	0.0000
R-squared	0.9978	
Percent of funds with Alpha significant > 0	43.1 %	
Percent of funds with Alpha significant < 0	2.0 %	

Appendix 8

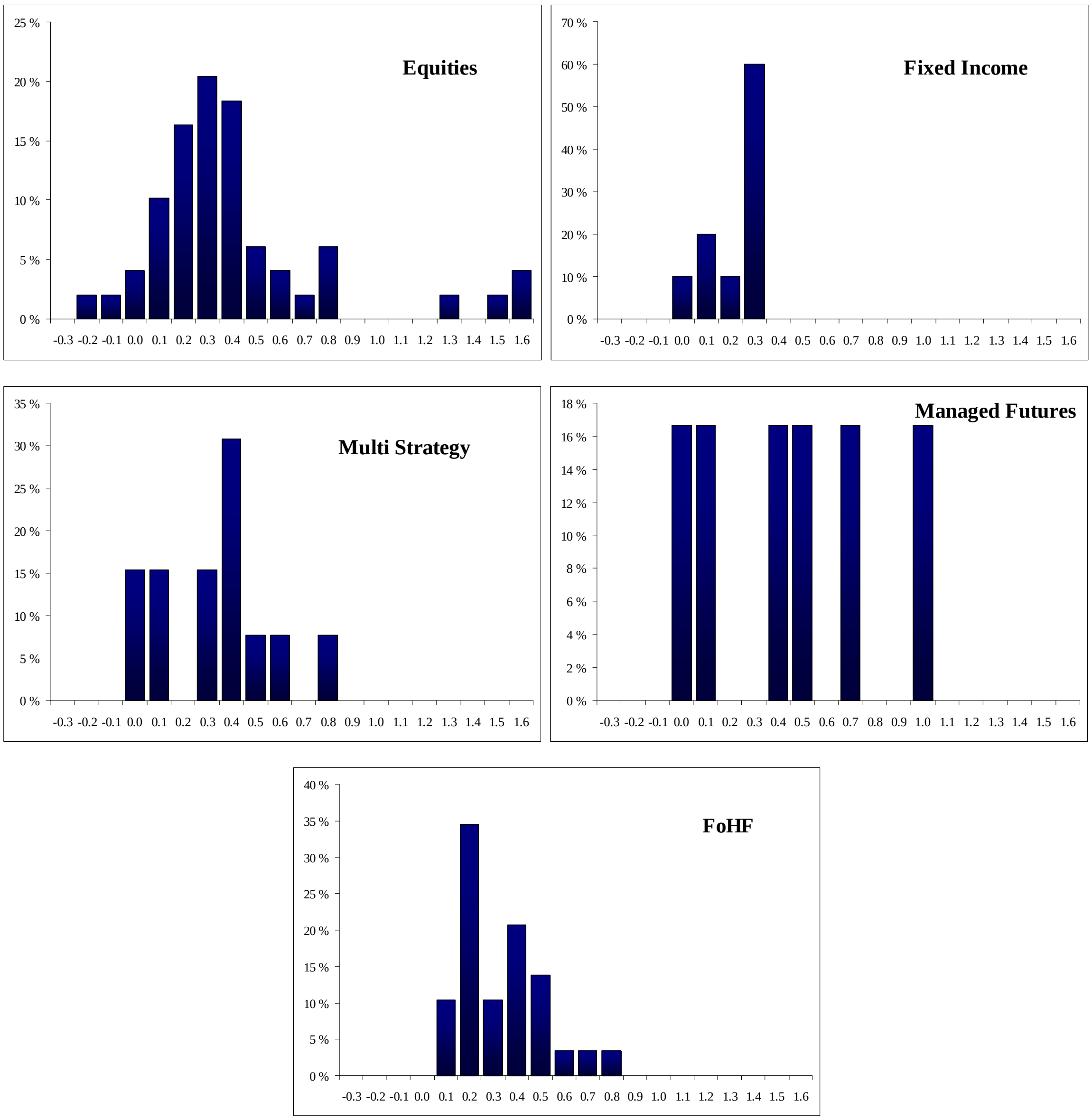
Coefficients/loadings from the multiple regressions for standard market exposure. Bold numbers indicate significance.

	MSCI World	MSCI Nordic	MSCI Emerging Markets	MSCI World Small Cap	MSCI Nordic Small Cap	Lehman US Government
Equities	-0.172	**0.275**	-0.109	-0.029	**0.240**	-0.246
Fixed Income	0.058	0.151	-0.071	-0.130	0.043	-0.059
Multi Strategy	0.008	**0.136**	-0.085	-0.096	**0.163**	-0.191
Managed Futures	-0.268	-0.048	-0.008	-0.111	**0.287**	0.112
FoHF	-0.203	**0.131**	0.002	**0.423**	-0.019	0.330
Composite	-0.132	**0.171**	-0.044	0.025	**0.149**	-0.051

Cont.	Lehman US High Yield	Handelsbanken Nordic	Bloomberg European Commodity Index	IPE Brent Crude Oil	Englehard Gold Bullion Spot	CBOE SPX Volatility Index
Equities	-0.018	**0.440**	0.005	-0.051	0.065	0.057
Fixed Income	0.132	**0.950**	-0.125	**0.097**	**0.140**	0.001
Multi Strategy	0.030	**0.757**	-0.089	0.047	0.064	-0.003
Managed Futures	0.136	**1.245**	-0.052	0.009	**0.222**	-0.026
FoHF	-0.081	0.128	-0.028	0.035	0.086	0.021
Composite	-0.018	**0.525**	-0.058	0.015	0.080	0.024

Appendix 9

Distributions of estimated individual stock-beta within every hedge fund style.



Appendix 10

Distributions of estimated individual bond-beta within every hedge fund style.